RISK TOLERANCE AND ASSET ALLOCATION

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Economics)
in The University of Michigan
2007

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ACKNOWLEDGMENTS

In writing this dissertation, I have benefited from countless discussions with my advisor, Matthew Shapiro, and my other committee members, Miles Kimball, Gary Solon, and Tyler Shumway. The lessons that I have learned from them about academic scholarship are far more valuable to me than the details of my dissertation. I am indebted to my committee members for the unique ways that they have each contributed to my intellectual development. Miles' unbridled enthusiasm for knowledge helped push me through the daily grind of research and reminded me of the larger quest. Gary's adamant critiques of my failed starts led to a substantially better dissertation and made the eventual successes even sweeter. Tyler's comments on the literature, particular in finance, brought some very useful research to my attention and highlighted for me the cumulative nature of scholarship. And above all, Matthew's insight, high standards, and generosity have had a profound impact on my journey over the past six years from student to researcher.

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CHAPTER I

Introduction

Economic theory assigns a central role to risk preference in asset allocation. This dissertation includes three papers that investigate this relationship empirically. The first paper uses panel data on hypothetical gambles over lifetime income in the Health and Retirement Study to quantify changes in risk tolerance over time and differences across individuals. The maximum-likelihood estimation of a model with correlated random effects draws on detailed information from 12,000 respondents in the 1992-2002 HRS. The results support constant relative risk aversion and earlier career selection based on preferences. While risk tolerance changes with age and macroeconomic conditions, persistent differences across individuals account for 73% of the systematic variation in preferences. The measure of risk tolerance also relates to actual stock ownership.

The second paper develops a measure of relative risk tolerance using responses to hypothetical income gambles in the HRS. In contrast to most survey measures that produce an ordinal metric, this paper shows how to construct a cardinal proxy for the risk tolerance of each survey respondent. The paper also shows how to account for measurement error in estimating this proxy and how to obtain consistent regression estimates despite the measurement error. The risk tolerance proxy is shown to explain differences in asset allocation across households.

The third paper investigates whether the characteristics of household labor income can account for the observed heterogeneity in financial portfolios. Households differ substantially in the riskiness of their labor income and in the magnitude of their labor income relative to their financial assets; however, the results of this paper suggest that households do not integrate their human capital in their financial asset allocation. This analysis uses a direct, household-level comparison between actual stock allocations and predicted allocations in three economic models with different assumptions about labor income. When labor income is excluded from the model, the correlation between actual and predicted stock allocations is 0.16. The inclusion of certain or risky labor income in the model leads to negative correlations of -0.12 and -0.06 respectively. There is no evidence that households take a broad view of wealth and diversify risks across their financial assets and human capital.

CHAPTER II

Stability of Risk Preference

2.1 INTRODUCTION

> "One does not argue over tastes for the same reason that one does not argue over the Rocky Mountains — both are there, will be there next year, too, and are the same to all men." Stigler and Becker (1977)

This paper approaches the fundamental debate on preference stability as an empirical question. I use a series of hypothetical gambles over lifetime income that have been fielded in the Health and Retirement Study (HRS) for more than a decade to quantify the degree and sources of change in individual risk preferences.[1] These gambles are specifically designed to measure risk preference and thus more cleanly identify the preference parameter than standard behavioral data from surveys or experiments (Barsky, Juster, Kimball and Shapiro 1997). The gamble explicitly states the riskiness of the choices, adopts the familiar situation of a job choice, and poses large, albeit hypothetical, stakes over lifetime income. The responses to the gambles — arguably the most objectively consistent set of risky choices embedded in a large panel study — allow me to characterize the systematic changes in risk tolerance over time for an individual, as well as the persistent differences in risk tolerance across a diverse group of individuals.

Specifically, I interpret the discrete choices in the gambles as a noisy signal of the individual's coefficient of relative risk tolerance from a standard economic model, as in Barsky et al. (1997) and Kimball et al. (2007).[2] Unlike any previous analysis of these data, I use the

[1] The Health and Retirement Study began in 1992 as a large biennial panel survey of Americans over the age of 50 and their spouses. Further information on the survey and the data are available at http://hrsonline.isr.umich.edu.

[2] The modeling of the survey response errors is particularly important here, since the gambles ask about hypothetical and

panel of gambles to quantify systematic changes in an individual's risk tolerance. I model risk tolerance with a time-varying component and a time-constant component. The panel of gamble responses and other detailed information from the respondents allows me to separate the within-person and across-person variation in preferences. Specifically, I estimate a correlated random effects probit with 18,625 gamble responses from 12,003 individuals between the ages of 45 and 70 across six waves of the HRS from 1992 to 2002.

The results present a nuanced view of the stability in risk preference. There is a modest decline in risk tolerance with age and an improvement in macroeconomic conditions is associated with an increase in risk tolerance. But changes in income and wealth do not measurably alter an individual's willingness to take risk. In addition, major life events of a job displacement and the diagnosis of a serious health condition that likely reduce expected lifetime income have little impact on measured risk tolerance. The invariance of risk tolerance to within-person changes in income — the explicit stake of the gamble — provides support for the specification of utility with constant relative risk aversion. While the gamble responses reveal few sources of systematic change in risk preference, there is substantial evidence of large persistent differences in preferences across individuals. Demographics, including gender, race, education, and marital status are all associated with significant differences in the time-constant component of risk tolerance. The panel also points to the past selection of risky careers and high debt levels based on the individual's risk tolerance type. Altogether, the time-varying attributes account for only 27% of the systematic variation in risk tolerance. There are also large persistent differences across individuals in their willingness to take risk in the hypothetical gambles that is not explained by any of the observables. The time-constant variance of preferences from the gambles that is unrelated to observables is twice as large as the systematic variance of preferences.

To validate externally the results from the hypothetical income gambles, I compare my individual measure of risk tolerance to the actual decision to own stocks. As theory predicts,

abstract scenarios from which individuals receive little financial benefit and may incur substantial costs from careful deliberation.

more risk tolerant individuals are more likely to own stocks and increases in an individual's risk tolerance increase the probability of stock ownership. The individual measure of risk tolerance also refines the standard inference on the correlates of stock ownership. Differences in risk tolerance explain the higher rate of stock ownership among men, but wealth and education remain important predictors of stock ownership even with the preference measure. While risk tolerance has a significant impact on stock ownership, the results also suggest a role for non-preference sources of variation, such as transaction costs and risk perceptions. In addition, this application demonstrates that a small set of hypothetical questions can capture meaningful variation in preferences both across individuals and over time that applies to an actual risky decision.

My analysis of the hypothetical income gambles contributes to a small empirical literature on the stability of risk preferences. The three comparable papers represent a range of different types of choice data and time horizons. In an experiment with small-scale monetary stakes, Harrison et al. (2005) find that over a six month period there is no significant shift in the risk preferences of 31 subjects. My results — with a larger panel of 12,003 individuals over a decade — also point to a substantial degree of temporal stability in risk preference. In addition, the richness of the HRS allows me to examine how specific events might alter an individual's risk preference. Unlike my results of relative stability in preferences, the analysis by Post et al. (2006) of 84 contestants on the game show "Deal or No Deal?" finds that recent events in the game strongly influence a contestant's subsequent risk taking. Their finding of path-dependent preferences agrees with other game shows studies, such as Gertner (1993), and Thaler and Johnson's (1990) experiments with student subjects. In contrast, my study shows that major life events, such as a job displacement or the diagnosis of a serious health condition, do not permanently alter the willingness to take further risks. An individual's risk tolerance is also unaffected by changes in income and wealth even though lifetime income is the explicit reference point in the gamble question. More similar to my results, Brunnermeier and Nagel (2006) find that transitory increases in wealth do not increase risk taking in household asset allocation. Their work fits in a large literature initiated by Friend and Blume (1975) that uses actual asset allocation decisions to infer information on preferences. But the portion of portfolio changes that reflect an active decision by households is imperfectly observed and thus complicates the inference on risk preference. My analysis of the hypothetical gambles — a very different type of data than actual portfolio choices — also finds support for the utility specification of constant relative risk aversion. The diverse work in this literature points to both a time-varying and a permanent component in risk taking. The goal of my research is to empirically quantify the magnitude of these components and investigate specific sources of variation.

The plan of the paper is as follows. Section 2.2 discusses the hypothetical gambles in the HRS. Section 2.3 uses expected utility theory to map the gamble responses to the coefficient of relative risk tolerance. The section then develops a statistical model of risk tolerance based on the gamble responses. Section 2.4 presents the results from maximum-likelihood estimation of the model. Section 2.5 uses the estimates of risk tolerance to study the household's actual decision to own stocks. The final section offers conclusions.

2.2 GAMBLES OVER LIFETIME INCOME

The Health and Retirement Study uses hypothetical gambles over lifetime income to elicit risk attitudes. In a short series of questions, individuals choose between two jobs; one job guarantees current lifetime income and the other job offers an unpredictable, but on average higher lifetime income. In the 1992 HRS, individuals consider the following scenario:

> Suppose that you are the only income earner in the family, and you have a good job guaranteed to give you your current (family) income every year for life.
>
> You are given the opportunity to take a new and equally good job, with a 50-50 chance it will double your (family) income and a 50-50 chance that it will cut your (family) income by a third. Would you take the new job?

Individuals who accept the first risky job then consider a job with a larger downside risk of one-half. Those who reject the first risky job are asked about a job with a smaller downside risk of one-fifth. Starting with the 1994 HRS, individuals who reject their first two risky jobs consider a third job that could cut their lifetime income by one-tenth. Likewise individuals who accept their first two risky jobs consider a third job that could cut their lifetime income by three-quarters. I use these responses to order individuals in a small number of categories. Table 2.1 relates the gamble response category to the downside risks that the individual accepts and rejects. The category numbers are increasing in an individual's willingness to accept income risk, so the gamble responses provide a coarse ranking of individuals by their risk preference.

Barsky et al. (1997) designed the gambles and analyzed the responses on the first two waves of the HRS. They acknowledge the potential for a status quo bias in the gamble responses due to the question wording, since individuals may have an aversion to a *new* job unrelated to its income risk. The 1998 HRS revised the hypothetical scenario so that individuals now choose between two new jobs:

> Suppose that you are the only income earner in the family. Your doctor recommends that you move because of allergies, and you have to choose between two possible jobs.
>
> The first would guarantee your current total family income for life. The second is possibly better paying, but the income is also less certain. There is a 50-50 chance the second job would double your total lifetime income and a 50-50 chance that it would cut it by a third. Which job would you take — the first job or the second job?

The objective attributes of the two jobs are identical in the original and revised versions of the question. Furthermore the 1998, 2000, and 2002 HRS use the same sequence of downside risks for the second job as the 1994 HRS uses for the new job. Over 30% of the individuals respond to both versions of the question which allows me to estimate the size of the status quo bias in the original question.

In this paper, I analyze 18,625 gamble responses on the 1992, 1994, 1998, 2000, and 2002 waves of the HRS from 12,003 individuals in the 1931 to 1947 birth cohorts.[3] The panel is

[3] In 1992 the HRS has a representative sample of individuals age 51 to 61, that is, the 1931 to 1941 birth cohorts, plus their spouses. The spouses are not necessarily representative of their birth cohort. The HRS periodically updates its sample

unbalanced due to survey attrition, expansion of the survey in 1998, and targeted delivery of the gamble questions in the survey. In particular, the survey usually asks the gambles to new respondents and a random sub-sample of returning respondents. Nonetheless 45% of the individuals answer the battery of income gambles in multiple waves and 8% answer the gambles in three or more waves.

The distribution of gamble responses in Table 2.2 shows that most individuals are unwilling to take income risks even when the expected value of the gamble is substantially larger than their current lifetime income. In 1992, more than two-thirds of individuals reject the risky job that offers a 50-50 chance to double lifetime income or cut it by one-fifth. The expected value of the income from this risky job is 140% of current lifetime income. And less than 13% of individuals accept the risky job with a downside risk of one-half which has an expected value of 125% of current lifetime income. The distribution of the gamble response categories is fairly stable across waves, though individuals in 1998 are willing to accept somewhat more income risk.

The placement of these gambles on a large panel study provides an ideal opportunity to study systematic changes in risk tolerance, and the decade in which the gambles are fielded coincides with many significant changes in individual circumstances and macroeconomic conditions. Table 2.3 summarizes the primary set of individual attributes and events that I use to quantify systematic changes in risk tolerance. First the considerable diversity in the sample of gamble respondents in the HRS is worth noting. Of the 18,625 gamble responses, 43% are from men, 15% are from blacks, and 8% are from Hispanics.[4] About one-fifth of the responses are from individuals with less than twelve years of education versus one-fifth from individuals with sixteen or more years of education.

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to maintain a snapshot of Americans over age 50. Starting in 1998, the HRS has a representative sample of individuals in the 1942 to 1947 birth cohorts that includes some of the spouses surveyed in earlier waves of the HRS. I use all of the survey responses from individuals in the 1931 to 1947 cohorts across the first six waves. I exclude the gamble responses of spouses outside these birth cohorts, as well as the representative sample of individuals in the 1921 to 1929 cohorts, since they are mostly retired at their initial survey and some express difficulty with the job-related gambles. To insure that the gamble is defined over non-trivial amounts of income, I also exclude individuals with total income less than $6,500 in 2002 dollars (or roughly the fifth percentile of income) at the time of their gamble responses or as an average across the six survey waves. The sample selection criteria have qualitatively little effect on the results.

[4]The HRS over-samples blacks, Hispanics, and residents of Florida. The tabulations and estimation in the paper place equal weight on each gamble respondent and do not reflect the distribution of attributes in the population.

Over the panel, several individuals have experiences that plausibly alter their expected lifetime income. I focus particularly on job displacements and serious health conditions. While an individual's past behavior may influence the occurrence of these events, they are not perfectly predictable and should represent some shock to an individual. Prior to their gamble response, 25% of the respondents had experienced a job displacement, that is, a job ending with a firm closure or layoff, and 22% had received a diagnosis of heart disease, a stroke, cancer, or lung disease. Most importantly, 13% of the gamble responses were followed later in the survey by a first job displacement for the individual and 17% by a first diagnosis of a serious health condition. This within-person variation is what allows me to identify the direct effect of these events on an individual's risk tolerance. Table 2.3 also shows that there are meaningful changes in income and wealth during the panel period.[5] On average, the household income and wealth of the respondents at the time of their gamble response is below the average levels of their total income and wealth across the 1992 to 2002 survey waves. But there is substantial variation across respondents in both the average level and changes in income and wealth.

The gamble responses also coincides with significant changes in the macroeconomy. Performance of the U.S. stock market particularly defined the survey period of April 1992 to February 2003. Figure 2.1 depicts the large increase and then sharp decline in the annual real returns on the S&P 500 Index. The shaded areas on the figure denote months in which the HRS asked the income gamble questions. The gambles appear on five waves of the HRS and each wave spans 8 to 15 months. This yields meaningful variation both across and within survey waves. Figure 2.1 also highlights positive association between consumer sentiment and stock market returns. I use the Index of Consumer Sentiment (ICS) in the month of an individual's interview to measure the general economic condition at the time of a gamble response.[6] There is considerable variation in general economic outlook both across

[5]Wealth is the total household net worth including housing wealth and excluding pension and Social Security wealth. Income is the total income of a respondent and spouse from all earnings, transfers, and other sources of income. Wealth and income are from the RAND HRS data set and include imputed values.

[6]A description of the index is available at the Survey of Consumers (www.sca.isr.umich.edu). Howrey (2001) demonstrates that the index has predictive power for economic recessions. Other indicators of the macroeconomic conditions, such as the

and within survey waves. From October 1992 to February 2000 the index rose sharply from 70.3 to 111.3 and over the course of the 2002 HRS the index dropped sharply from 96.9 in May 2002 to 79.9 in February 2003.

2.3 MODEL OF RISK TOLERANCE

In this section, I discuss how I use the gamble responses on the HRS to quantify changes in an individual's risk tolerance over time, as well as differences across individuals at a point in time. I adopt the expected utility interpretation of the gambles and the general estimation strategy developed by Barsky et al. (1997) and later used in Kimball et al. (2007). I use a rich set of covariates to investigate systematic changes in risk tolerance. My model incorporates the potential correlation between the time-constant component of risk tolerance and other time-varying attributes. The estimates from a panel of gamble responses and attributes allow me to determine whether a change in individual circumstances leads to a change in risk tolerance or simply signals an individual's risk tolerance type.

2.3.1 Mapping Gambles to Preferences

Expected utility theory offers a translation of an individual's gamble responses to a standard metric of risk preference — the coefficient of relative risk tolerance. Specifically, choices in the gambles establish a range for an individual's risk tolerance. Consider a general utility function U and a level of permanent consumption c. Offered a 50-50 chance of doubling lifetime income or cutting it by a fraction π, an individual accepts a risky job when its expected utility exceeds the utility from the certain job, that is, if

$$0.5U(2c) + 0.5U((1-\pi)c) \quad \geq \quad U(c). \tag{2.1}$$

The greater the curvature of U, the smaller the downside risk π an individual accepts. This interpretation of the gamble responses links lifetime income to permanent consumption and ignores the potential effect of wealth.[7] To quantify risk preference, I assume that relative risk

unemployment rate or real return on the S&P 500 provide qualitatively similar results.

[7]As a sensitivity check, I model wealth explicitly in the argument of the utility function, such that $c \propto y + \phi w$, where y is the current total household income and w is 5% of total household net worth (or an approximate annuity value of wealth).

aversion (and its reciprocal relative risk tolerance) are constant in the range of the gambles, such that

$$U(c) = \frac{c^{1-1/\theta}}{1-1/\theta} \tag{2.2}$$

The coefficient of relative risk tolerance, $\theta = -U'/cU''$ (Pratt 1964), in this specification of utility may differ across individuals. It is assumed to be constant for all values of permanent consumption for a given individual. The estimated model of risk tolerance in Section 2.4, which includes measures of income and wealth, is consistent with this assumption of constant relative risk aversion utility.

In this framework, the gamble responses define a range for an individual's risk tolerance θ. Consider an individual, in gamble response category 3, who accepts the job with a one-fifth downside risk and rejects the job with a one-third downside risk. These choices imply a coefficient of relative risk tolerance between 0.27 and 0.50, since

$$\underline{\theta}_3 = 0.27 \iff 0.5\frac{2^{1-1/\underline{\theta}_3}}{1-1/\underline{\theta}_3} + 0.5\frac{(1-1/5)^{1-1/\underline{\theta}_3}}{1-1/\underline{\theta}_3} = \frac{1^{1-1/\underline{\theta}_3}}{1-1/\underline{\theta}_3} \tag{2.3}$$

$$\overline{\theta}_3 = 0.50 \iff 0.5\frac{2^{1-1/\overline{\theta}_3}}{1-1/\overline{\theta}_3} + 0.5\frac{(1-1/3)^{1-1/\overline{\theta}_3}}{1-1/\overline{\theta}_3} = \frac{1^{1-1/\overline{\theta}_3}}{1-1/\overline{\theta}_3}\,. \tag{2.4}$$

The highest downside risk accepted and the smallest risk rejected establish the upper and lower bounds on risk tolerance. The last two columns of Table 2.1 provides the range of risk tolerance for each of the gamble response categories.

2.3.2 Model of Measured Log Risk Tolerance

The statistical model of risk tolerance θ_{it} encompasses systematic changes in preferences and a persistent attitude toward risk, such that,

$$\log\theta_{it} = x_{it}\beta + a_i \tag{2.5}$$

where $x_{it}\beta$ is the time-varying component and a_i is the time-constant component of the logarithm of risk tolerance. The logarithmic specification of risk tolerance captures the fact

The estimated weight on wealth ϕ is 0.019 and is not statistically different from zero at the 5% level. Annuitization based on a life table and the respondent's age has no qualitative effect on the estimated weight. Thus the simplifying assumption of approximating consumption with income is appropriate when interpreting the gamble responses.

that most individuals exhibit a low tolerance of risks in the gambles, but some individuals are willing to take large income risks. The parameter β measures the percent change in risk tolerance associated with a change in the attributes x_{it}.

The time-constant component of risk tolerance a_i may be correlated with the individual circumstances x_{it} that can change risk tolerance. For example, the experience of a job displacement may reduce an individual's willingness to take further risks, that is, $\beta < 0$. Or the event could primarily reveal an individual's risk tolerance type if more risk tolerant individuals tend to select career paths with a higher risk of displacement. To accommodate such selection effects, I model a relationship between the time-constant component a_i and observable attributes as

$$a_i = \overline{x}_i \lambda + u_i \tag{2.6}$$

where $\overline{x}_i$ is the panel average of $x_{i1}, ..., x_{iT}$ for individual i and the type effect λ measures the persistent systematic differences across individuals in risk tolerance.[8] The term u_i captures the portion of constant risk tolerance a_i that is unrelated to the attributes in $\overline{x}_i$, a vector that includes a constant. This mean-zero residual is constant for a given individual over time and is independently distributed across individuals conditional on observables, such that, $u_i|\overline{x}_i \sim \mathrm{N}(0, \sigma_u^2)$. The model of the correlated random effects in equation (2.6) follows from Mundlak (1978). Chamberlain (1984) summarizes this modeling strategy and presents a more general specification of the type effects.[9]

The estimation strategy also recognizes the limitations of using a small set of hypothetical gambles responses to infer individual preferences. First, the gamble responses establish an interval, not a point estimate, for risk tolerance, so I do not have the data to simply estimate the linear model. Second, the income gamble questions likely generate substantial survey

[8] The panel is unbalanced, so the average is $\overline{x}_i = (1/T_i \sum_{j=1}^{T} w_{it} x_{it})$, where T_i is the number of survey waves for individual i and w_{it} is an indicator for participation in wave t. I include information on an individual's circumstances from the first six waves of the HRS, not just the waves in which an individual answers the income gambles. To make the estimated effects of an event easier to interpret, I define x_{it} as an event prior to time t and $\overline{x}_i$ as an event before the end of the panel.

[9] Specifically, Chamberlain controls for the full set of an individual's covariates $x_{i1}, ..., x_{iT}$, not just the panel average, which yields estimates of the type effects that can vary over time or λ_t. One limitation of the general specification is the need for a balanced panel of the observables x_{it}. This restriction would have reduced my sample of gamble respondents by 46%, so I use the more parsimonious form of the correlated random effects with the panel average of observables.

response error as is common with hypothetical and cognitively difficult questions. Nearly half of the individuals switch their gamble responses across waves — one sign of random noise. Comments made by individuals during the survey also highlight difficulties respondents had in answering the hypothetical income gamble questions.[10] Survey response errors can arise on the gambles when individuals misinterpret the hypothetical scenario or make computational mistakes in their comparison of the jobs.

To incorporate these additional features of the data, I model the latent signal ξ_{it} from the individual's gamble responses as a combination of risk tolerance θ_{it} and a survey response error ϵ_{it}, such that

$$\xi_{it} = \log\theta_{it} + \epsilon_{it} \tag{2.7}$$

$$c_{it} = j, \quad \text{if} \quad \log\underline{\theta}_j < \xi_{it} < \log\overline{\theta}_j \quad (i = 1, ..., N; t = 1, ...T) \tag{2.8}$$

where c_{it} is the gamble response category that is observed in the data. An individual in response category j has a noisy signal of risk tolerance that lies in the interval $(\log\underline{\theta}_j, \log\overline{\theta}_j)$, where the cutoffs are the logarithm of the values in Table 2.1. The odds and outcomes are explicit in the gamble questions, so with the assumption of constant relative risk aversion utility, the intervals of risk tolerance are known values and do not vary across individuals or across waves. The model of the latent signal incorporates two sources of variation in the gamble responses over time: systematic changes in risk tolerance and survey response error. Earlier studies of the income gambles by Barsky et al. (1997) and Kimball et al. (2007) on the HRS also model the time variation in gamble responses due to response error. My analysis is the first to investigate changes in risk tolerance that are both systematically associated with observed changes in circumstances and due to the random variation from response errors. For identification, I assign all the changes in the latent signal that are unrelated to these covariates to the survey response error. This assumption likely understates any high

[10]Examples from the 1998 HRS interviewer records include: "I'd take the one with more money," "It's too hard for me over the phone," and "I don't have experience. Anything without experience I can't answer." The interviewer records comments made by the respondent at each question. In the 1998 HRS, there were comments to the gambles from less than 8% of individuals and many entries only noted a repetition of the question. This para-data is restricted access and its availability varies across waves. For further information contact hrsquest@isr.umich.edu.

frequency shifts in risk tolerance. My focus on the time-constant and systematic variation in preferences is consistent a well-defined measure of risk preference that would apply to other risky decisions made by the individual.

In modeling the survey response error, I also investigate the question framing effects and heteroscedasticity in the response error. The survey response error ϵ_{it} has the form

$$\epsilon_{it} = q_{it}\delta + e_{it} \tag{2.9}$$

where q_{it} is an indicator for a gamble response to the original ("new job") version of the question, so δ measures the degree of status quo bias in responses to the gamble question on the 1992 and 1994 HRS.[11] The term e_{it} is a survey response error that is unrelated to both the question type and other observables. It is independently distributed $\mathrm{N}(0, \sigma_{eit}^2)$ across individuals and over time. I allow the observed attributes in the model of risk tolerance and the question type to also affect the dispersion of the response error. Specifically, the dispersion in response errors is $\sigma_{eit} = \exp[(x_{it}, \overline{x}_i, q_{it})\sigma_e]$, where σ_e is a parameter vector that relates individual attributes to the variation in response errors. Thus individuals with a particular attribute, such as less education, do not systematically understate (or overstate) their risk tolerance in their gamble responses. The response errors in this group, however, may be larger in absolute value than the response errors from individuals with more education. The term e_{it} soaks up changes in an individual's gamble responses that are not associated with the observed attributes, as well as the unsystematic transitory variation in the gamble responses across individuals. The heteroscedastic variance of e_{it} permits the precision in the gamble responses — or the degree of wave-to-wave switches — to vary with individual attributes and question type. The gambles are complicated hypothetical questions on a lengthy survey and answers to the gambles have no real consequences, so a careful treatment of the survey response error is essential to infer risk tolerance from the gamble responses.[12]

[11] Features of the gamble delivery, such as a face-to-face or a telephone interview, or differences in respondent's survey behavior, such as time to complete the interview and frequency of item non-response, could also be included in q_{it}. For covariates that systematically affect both preferences and response errors, it would not be possible to separately estimate β and δ.

[12] Previous research also finds that the use of hypothetical questions leads to more variance in responses — not a systematic bias in the responses. In their survey of experimental studies, Camerer and Hogarth (1999) find that the size of financial incentives does not affect the average performance on judgment tasks. But smaller financial incentives are associated with

Combining the models of risk tolerance and survey response error yields a reduced-form description of the latent signal in the gamble responses:

$$\xi_{it} = x_{it}\beta + a_i + q_{it}\delta + e_{it} \tag{2.10}$$

$$= x_{it}\beta + \overline{x}_i\lambda + q_{it}\delta + u_i + e_{it} \tag{2.11}$$

A restatement of the model draws particular attention to the variation in the preference signal within and between individuals. Specifically,

$$\xi_{it} = (x_{it} - \overline{x}_i)\beta + \overline{x}_i(\lambda + \beta) + q_{it}\delta + u_i + e_{it} \tag{2.12}$$

where the first term $(x_{it} - \overline{x}_i)\beta$ captures a change in risk tolerance for a given individual and the second term $\overline{x}_i(\lambda + \beta)$ captures the differences in risk tolerance across individuals that are associated with observed attributes. The separate identification of the direct effect β and the type effect λ depends crucially on variation in x_{it} over the panel period and variation in $\overline{x}_i$ across the individuals. For time-constant attributes, such as gender and race, or choices made before the survey period, such as years of education, I can only identify the composite term of $(\beta + \lambda)$, not the direct effect β. In contrast, the type effect λ of a covariate is not identified when its panel average $\overline{x}_i$ is the same for all individuals. For example, the gamble respondents all experienced the same macroeconomy of the 1990s, so any association between the average economic outlook in the panel and the persistent component of risk tolerance is absorbed in the estimate of the constant.

2.3.3 Log-Likelihood of Gamble Responses

I use maximum-likelihood methods to estimate the parameters $(\beta, \lambda, \delta, \sigma_u, \sigma_e)$ of the reduced-form model in equation (2.11) with the panel of income gamble responses and covariates. I compute the probability of observing an individual's set of gamble responses over the survey period with a truncated normal distribution function, where the order of the function corresponds to the number of waves (up to five) in which an individual answers the

greater variance or noise in the responses. Similarly Dohmen et al. (2006) establish a strong but imperfect correlation between the responses to hypothetical gambles on a large survey and gambles in an experiment with actual payoffs.

income gambles. Consider, for example, an individual who answers the gambles in only one wave of the HRS, but participates in multiple waves of the survey. The attributes x_{it} that are observed with a response to version q_{it} of the income gambles and the average of these attributes across the entire panel $\overline{x}_i$ yield the following likelihood that the individual is in gamble response category j at time t:

$$\begin{aligned} P(c_{it} = j|x_{it}, \overline{x}_i, q_{it}) &= P(\log \underline{\theta}_j < \xi_{it} < \log \overline{\theta}_j | x_{it}, \overline{x}_i, q_{it}) \\ &= \Phi\left(\frac{\log \overline{\theta}_j - x_{it}\beta - \overline{x}_i\lambda - q_{it}\delta}{\sigma_{\xi it}}\right) - \Phi\left(\frac{\log \underline{\theta}_j - x_{it}\beta - \overline{x}_i\lambda - q_{it}\delta}{\sigma_{\xi it}}\right) \end{aligned} \tag{2.13}$$

where $\sigma^2_{\xi it} = \text{Var}(\xi_{it}|x_{it}, \overline{x}_i, q_{it}) = \sigma^2_u + \sigma^2_{eit}$ and $\Phi(\cdot)$ is the univariate normal cumulative distribution function. I adjust the likelihood function accordingly for the individuals who answer the gamble questions in multiple survey waves.[13] Since the lower bound $\log \underline{\theta}$ and upper bound $\log \overline{\theta}$ for the latent signal in each response category are known, the mean effects of β, λ, and δ are identified separately from the variance terms and are interpretable as if the latent signal ξ_{it} were directly observed.[14] Given the model of preferences, the estimate of β is the percent change in risk tolerance for a given individual due to a change in x_{it} and λ is the percent difference in risk tolerance across individuals due to a difference in $\overline{x}_i$.

The maximum-likelihood estimator finds the values of the parameters that maximize the conditional log-likelihood $\mathcal{L}$ of the sample:

$$\mathcal{L}(\beta, \lambda, \delta, \sigma_u, \sigma_e | c_i, x_{it}, \overline{x}_i, q_{it}) = \sum_{i \in N} \sum_{j \in J} 1[c_i = j] \log P(c_i = j | x_{it}, \overline{x}_i, q_{it}) \tag{2.14}$$

where $c_i = (c_{i1}, ...c_{iT})$ is the set of an individual's gamble responses on the HRS and J contains all possible sets of response categories. For the estimator, I use the modified method of scoring, a Newton-Raphson algorithm in which the sample average of the outer product from the score function approximates the information matrix.[15] The estimates of the asymptotic

[13]The individual-specific random effect u_i is constant over time, such that the $\text{Cov}(\xi_{is}, \xi_{it}|x_{is}, x_{it}, \overline{x}_i, q_{is}, q_{it}) = \sigma^2_u$ for $s \neq t$. To simplify the computation of the higher order probabilities, I integrate the product of the univariate densities conditional on u_i over the distribution of u_i. See Cameron and Trivedi (2005) for a further discussion of this standard method. For the integration, I use Matlab codes for Gaussian quadrature from Miranda and Fackler (2002). I use correlated random effects for the probit model of gamble responses, since there is no consistent fixed-effects estimator, see Chamberlain (1984) for a discussion.

[14]In contrast, a standard ordered probit model also estimates the cutoffs, so only the ratio of the mean effects to the unobserved standard deviation is identified. Even with known cutoffs, the identification of σ_u and σ_e requires that at least some individuals respond to the gambles in more than one wave.

[15]I calculate the score with numerical differentiation code from Miranda and Fackler (2002) and implement the maximum-likelihood estimator in Matlab.

standard errors are also derived from this estimator of the information matrix.

2.4 ESTIMATES OF RISK TOLERANCE

The results from the maximum-likelihood estimation reveal a low degree of risk tolerance on average, although there is considerable preference heterogeneity across individuals. The mean of relative risk aversion in the sample is 9.6 and its standard deviation is also 9.6.[16] This implies that an average respondent would be willing to pay 28% of lifetime income to avoid a gamble with the 50-50 chance of doubling lifetime income or cutting it by one-third. It is possible that some feature in the framing, fielding, or modeling of the gambles may bias the estimated level of risk preference. Yet even with a persistent misstatement in the gamble responses, this panel of answers to the same question over a decade still provides valid information on the stability of individuals' preferences.

In this sample of older individuals, the gamble responses reveal few sources of systematic and long-lasting shifts in risk tolerance. I find a moderate decline in risk tolerance with age and a co-movement of individual risk tolerance and the macroeconomic conditions. But changes in the individual's total household income or wealth do not significantly alter an individual's willingness to take risk. In addition, a job displacement and diagnosis of a serious health condition, two personal events that plausibly reduce expected lifetime income, have little impact on risk tolerance. These results support the standard utility specification of constant relative risk aversion for within-person changes in consumption. I also find large stable differences across individuals in risk tolerance type that relate to commonly observed attributes. The estimated effects of time-constant observed attributes, such as gender and race, broadly conform to the results in earlier cross-sectional studies of risk attitudes. The panel structure of the HRS also reveals a relationship between individuals' earlier decisions, such as career choice, and their risk tolerance type. The rest of this section discusses the results from the maximum-likelihood estimation. The full model has 55 parameters, including

[16] See Kimball et al. (2007) for more details on the distribution of risk preference estimated with a similar sample of HRS gamble responses.

direct effects, type effects, and error variance effects related to 20 observed attributes, so I have chosen to present the results in pieces. Appendix Table 2.9 contains the full set of covariates and estimates.

2.4.1 Household Income and Wealth

The outcomes in the hypothetical gambles are defined as fractions of "your current family income every year for life," so the changes in income that individuals experience over the panel of gamble responses provide the power to test the utility specification of constant relative risk aversion. The gamble responses reveal no discernible change in risk tolerance when an individual's current income or wealth deviates from its average level in the panel.[17] The first column of Table 2.4 shows that a 10% increase in current income relative to the individual's average income is associated with only a 0.3% increase in risk tolerance. With a standard error of 0.3% the direct effect of a within-person change in income on risk tolerance is a precisely estimated zero effect. Likewise changes in an individual's current wealth have no discernible effect on risk tolerance. These results suggest that the assumption of constant relative risk aversion as consumption changes for a particular individual is justifiable.[18]

The gamble responses, however, do not imply that risk aversion is constant across individuals with different levels of consumption. There are modest and statistically significant differences in risk tolerance across individuals related to their level of average income and average wealth in the panel. A 10% higher level of average income is associated with a 0.9% higher relative risk tolerance – a pattern consistent with more risk tolerant individuals selecting higher risk, higher return sources of income. This effect is modest in size but is sta-

[17] The net value of total household wealth is the sum of all wealth minus all debts. Wealth components include value of primary residence, net value of other real estate, net value of vehicles, net value of businesses, and net value of financial assets (IRAs, stocks, CDs, bonds, cash, and other assets). Debts include value of all mortgages, value of other home loans, and value of other debts. Total household income includes earnings, employer pensions, Supplemental Security Income, Social Security disability and retirement, unemployment and workers compensation, and other government transfers for the husband and wife plus household capital income and other income. This analysis uses RAND HRS (Version F) data and imputations for wealth and income.

[18] The absence of an effect from changes in wealth could either signal a non-integration of wealth in the evaluation of the income gamble or provide support for CRRA. The hypothetical nature of the question may also play a role in the results. In an experimental study with actual and hypothetical stakes, Holt and Laury (2002) find that changes in the magnitude of the stakes lead to changes in an individual risk aversion only when the stakes are real, but not when they are hypothetical. The largest possible payoff to a single gamble in their experiment is \$346.50 and the largest change is the payoffs across their treatments is \$342.65. In contrast, the stakes in the HRS gambles are defined over lifetime income where the median level of current income is \$54,176 and the median deviation in current income from average income is \$2,167. The large difference in the scale of the risks between their study and mine complicates a direct comparison of the results.

tistically different from zero at the 5% level. Similarly, individuals with greater indebtedness reveal a higher level of risk tolerance in their gamble responses, with a 10% more negative average wealth associated with a 0.5% higher relative risk tolerance. There is no discernible pattern in risk tolerance across individuals with different, positive levels of average wealth. This could result from a cancelling of two effects: less risk tolerant individuals accumulate precautionary saving and more risk tolerant individuals select riskier, higher return assets.

These results from the HRS are comparable to previous cross-sectional studies of hypothetical choice data that find an association between the willingness to take risk and the level of income and wealth, including Donkers et al. (2001) and Dohmen et al. (2006). With different survey questions and modelling approaches in their cross-section studies, their point estimates are not directly comparable to my results. In general, the association between risk preferences and income or wealth in all of these studies is consistently small relative to demographics, such as gender and age.[19]

The second column of Table 2.4 investigates the robustness of the baseline estimates of income and wealth effects. The question frame of a hypothetical job choice may impede non-workers from revealing their true preferences and obscure an effect of income or wealth on risk tolerance. This issue could be particularly severe in the HRS where one-third of the individuals are not working at the time of their gamble response and over 40% experience a change in their work status during the panel. The estimates in the second column of Table 2.4 demonstrate that the risk tolerance of working household heads is no more sensitive to changes in income or wealth than the risk tolerance of all respondents. The direct effects of income and wealth in this sub-sample are not substantially altered and remain statistically indistinguishable from zero at the 5% level. The positive association between the logarithm of average income and risk tolerance does increases to 0.14 from 0.09. The type effect of negative wealth decreases to 0.01 from 0.05 and is no longer distinguishable from zero.

[19] In their index of risk aversion, Donkers et al. (2001) find that being 10 years younger has the same marginal effect as having 81% more income. On a qualitative general risk question and a hypothetical lottery question, Dohmen et al. (2006) find even smaller marginal effects, such that a one year difference in age is equivalent to more than a 75% difference in income or wealth. By my estimates, the decline in risk tolerance from a one year increase in age is equivalent to the decline in risk tolerance from current income 59% below average income or current wealth 49% below average wealth.

2.4.2 Job Displacement and Health Condition

I also examine the association between risk tolerance and two major life events, a job displacement and a serious health condition, that likely affect an individual's expected lifetime income.[20] The gambles on the HRS are defined over current lifetime income, so a shift in this reference point could alter an individual's attitude toward risk. For example, individuals may accept more income risk after a negative personal shock if that gamble could restore their original level of lifetime income. Or individuals who have received one draw of bad luck may simply be less willing to "spin the wheel" again.[21] Rather than a change in risk tolerance, these events — which do not occur purely at random — could also signal an individual's risk tolerance type. For example, high risk tolerant types may have selected riskier career paths with a higher chance of displacement, so they comprise a large fraction of the workers who actually experience displacements. Or more risk tolerant individuals may have forgone preventative health care, and thus accepted a higher risk of a serious health condition. A panel of gamble responses and events is essential for separating these mechanisms.

In Table 2.5 both a job displacement and the onset of a health condition are associated with a decline in risk tolerance of 6% and 9% respectively. These direct effects are imprecisely estimated and not statistically different from zero at the 5% level.[22] More striking is the evidence of selection into risky careers based on individual preferences. Among individuals with no prior job displacement at the time of their gamble response, those who will experience a displacement later in the panel are 19% more risk tolerant than those who will never experience a displacement. The estimate of the type effect is both economically and statistically significant, as it suggests that high risk tolerance types have systematically chosen riskier careers with a higher chance of displacement. The positive correlation between risk tolerance and income risk underscores the need for a direct measure of individual preferences.

[20] Several studies find that a job displacement lowers current and future earnings (Ruhm 1991), as well as reduces long-run consumption (Stephens 2001). Likewise Smith (2003) finds that a severe health event affects household income and wealth.

[21] Alternatively, a decrease in an individual's risk tolerance following a negative income shock could also follow from a model of internal habit formation.

[22] I define a job displacement as a job ending with a business closure or a layoff. The HRS provides information on up to two jobs prior to the initial interview, the job at each interview, and jobs between interviews. I define a serious health condition as heart disease, stroke, cancer, or lung disease. The HRS asks separately about these and other conditions.

For example, studies of household wealth accumulation that do not address this systematic variation in preferences would underestimate the amount of precautionary savings.[23] The estimated type effect of a serious health condition is only 2% and is not statistically different from zero at the 5% level.

I use the gamble responses that individuals provide before and after major life events to identify the impact of these events on risk tolerance. In an unbalanced panel, attrition could be systematically related to these events and thus to changes in risk tolerance. The second column of Table 2.5 presents the results from the model estimated with individuals who respond in all six waves of the HRS.[24] The balanced panel produces similar estimates of the type effects, but different estimates of the direct effects. The estimated direct effects imply a larger declines in risk tolerance of 11% after a job displacement and of 15% after the onset of a health condition. The direct effect of a health condition is now statistically significant. The bottom panel of Table 2.5 shows that the estimated type effects in the unbalanced and balanced panels are similar. In the balanced panel, individuals who will experience a job displacement later in the panel are 20% more risk tolerant and those who will experience the onset of a health condition are 6% more risk tolerant than individuals who will not experience the event before the end of the panel. As in the unbalanced panel, the across-person difference in risk tolerance that is revealed by a job displacement is statistically significant.

2.4.3 Age, Cohort, and Time

The ten-year panel of gamble responses also provides a unique opportunity to examine systematic changes in risk tolerance with age and with changes in the macroeconomic conditions. Yet, even with multiple observations from the same individuals, I face the standard challenge of separating the effects of age, birth cohort and time.[25] I model the time effects

[23] In a comparison of savings in the former East and West Germany after reunification, Fuchs-Schündeln and Schündeln (2005) also find evidence of job selection due to risk preferences. They also show that ignoring this selection would underestimate precautionary wealth by 40% among German households.

[24] Note that this is a balanced panel of information on job displacements, health conditions, and other demographics, but not on the income gambles. The income gambles are only asked in five of the six survey waves and not to all respondents.

[25] Age, birth cohort, and time form a perfect relationship, that is, age = year − birth year, so the separation of the effects requires further assumptions. See Hall et al. (2005) for a discussion of various identification strategies and other references.

with a measure of macroeconomic conditions at the time of the gamble response. I use a linear specification for the age effects and indicator variables that span five to six birth years for the cohort effects. The first column of Table 2.6 presents the estimates of the model. I find that each year of age is associated with a 1.7% decline in an individual's risk tolerance. This implies almost a 20% decrease in risk tolerance over the survey period associated with aging.[26] Individuals in the 1937-41 birth cohorts are also 16% more risk tolerant than individuals in the 1931-1936 cohorts. The effects of birth cohort are suggestive of individuals closer to the Great Depression being less willing to take risk. Finally there is a strong positive relationship between risk tolerance and macroeconomic conditions, as measured by the Index of Consumer Sentiment (ICS) in the month of the gamble response. A ten-point increase in the sentiment index is associated with a 9% increase in an risk tolerance. During the panel period, there are substantial movements in this measure of economic conditions which imply quantitatively important changes in average risk tolerance. For example, risk tolerance increased steadily by 36% from October 1992 to February 2000 and then decreased sharply by 15% from May 2002 to February 2003. The movements in risk tolerance over the business cycle are substantial in magnitude; however, they do not signal a permanent shift in an individual's risk tolerance. To explore the duration of the macroeconomic effects, the second column of Table 2.6 adds a measure of consumer sentiment at six months and one year prior to the gamble response. The strongest association of 0.006 (t-statistic of 2.2) is between current macroeconomic conditions and risk tolerance. The estimated effect declines to 0.004 (t-statistic of 1.6)and -0.001 (t-statistic of -0.4) for macroeconomic conditions at six months and one year prior to the gamble response respectively. These results suggest the effect of changes in the macroeconomic conditions on risk tolerance is short-lived.

Sample attrition that is related to an individual's risk tolerance, such as engaging in risky health behaviors that raise the chance of death, could also bias the estimates.

[26]In comments during the gamble sequences, some individuals explicitly recognize the effect of aging on risk tolerance: "Depends on how old you are. If you are 25, you gamble, but not now." and "If I were younger, I would take a chance." Other studies, including Barsky et al. (1997), Donkers et al. (2001), and Dohmen et al. (2006), also find that older individuals are less willing to take risks. But my analysis is the first to use within person variation in gamble responses to identify the effect of aging. Even though this analysis uses a rich set of covariates, there are several events that are correlated with aging and are not included in this model of risk tolerance. The current results show an negative association, but not a causal link, between aging and risk tolerance.

The last two columns of Table 2.6 use an alternate specification of the year effects that includes indicator variables for the survey wave. In the third column, the model controls for the survey wave of a gamble response, but not for consumer sentiment.[27] All of the year effects are economically and statistically significant. This alternate specification has only a modest impact on the point estimate for age and birth cohort. In the last column, the model includes both the indicators of the survey wave and the measure of consumer sentiment. Here the effect of macroeconomic conditions is identified entirely from within-wave variation. Nonetheless the estimate of 0.007 is only 17% lower than the estimate of 0.009 in the baseline model and is still statistically different from zero at the 5% level. In addition, the Index of Consumer Sentiment soaks up much the wave-to-wave differences in gamble responses. Only in the 1994 HRS do the gamble respondents remain significantly more risk tolerant than the gamble respondents in the 1992 HRS.[28] Again the estimated effects of age and birth cohort are not altered by different specification of the time effects. The comparison of the results in Table 2.6 demonstrates that my parsimonious model of age, cohort, and time in the first column captures the systematic change in individuals' risk tolerance with age and macroeconomic conditions.

2.4.4 Individual Attributes

While there are modest changes in risk tolerance, 73% of the systematic variation in preferences is driven by the time-constant differences across individuals. The estimates in the first column of Table 2.7 reveal substantial differences in risk tolerance by gender, race, and years of education. The relative risk tolerance of men is 14% higher than of women — a finding consistent with a vast literature on gender differences in risk taking; see Byrnes et al. (1999) for a meta-analysis of the studies in psychology. There is an even larger disparity in the willingness to take risk by race with blacks 28% less risk tolerant than whites. The

[27] In addition, I cannot control separately for the question version, since all the gamble respondents in the 1992 HRS and 1994 HRS answer the "new job" version of the question.

[28] The gambles on the 1994 HRS are asked in a module at the end of the survey. In the four other waves, the gambles appear near the end of the Cognition or Expectations Section of the core survey. This section is generally in the middle-end of the survey. Individuals are randomly selected to participate in the module in 1994, and they are explicitly given an opportunity to skip this extra section. The group of gamble respondents — and the environment of the question collection — in 1994 may not be entirely comparable to gamble responses on other waves.

income gambles on the HRS also reveal a strong positive association between education and risk tolerance, such that those with more than post-graduate education are 32% more risk tolerant than high school graduates. Other work that analyzes hypothetical risky choices and qualitative measures of risk taking on large-scale surveys, such as Dohmen et al. (2006) and Donkers et al. (2001), has found similar patterns for all three variables. My analysis is one of the few attempts to quantify these differences in terms of the coefficient of relative risk tolerance.[29]

Table 2.7 also provides the estimated effects of marital status on risk tolerance. Entering a marriage is associated with an 11% increase in risk tolerance, though the estimate is not statistically different from zero at the 5% level. Yet less risk tolerant individuals are more likely to be consistently married in the panel. All else equal, an individual who is married at each survey is 16% less risk tolerant than an individual who is never married and the selection effect is statistically significant.[30] Again this pattern is consistent with a stable attitude toward risk that influences actual behavior.

Finally there is a strong relationship between the measures of risk tolerance and probabilistic thinking skills in the HRS. Individuals who provide more precise answers to the subjective probability questions in the survey are also willing to take more risk on the hypothetical income gambles and exhibit less random variation in their gamble responses across survey waves. In my model of risk tolerance, I use the measure of probability precision developed by Lillard and Willis (2001), that is, the fraction of the subjective probability questions to which the individual provides an exact answer (not 0, 50, 100). There are roughly 20 such questions in each survey wave that cover future personal and general events. On average respondents only give exact answers to about 40% of the probability questions. Lillard and Willis (2001) use a model of uncertainty aversion to argue that individuals with

[29]In their study of the income gambles on the HRS, Barsky et al. (1997) compare their measure of an individual's risk tolerance — estimated from only the gamble responses — across several groups. Their findings are qualitatively similar to mine. In contrast to their univariate comparisons, my analysis of risk tolerance uses a multivariate maximum-likelihood model and a richer set of covariates.

[30]This calculation adds the estimated direct effect of 11% with the type effect of -27%. The comment data also provide evidence of how a family mitigates the desire to take risks, such as "If just I, gamble, but for family go with the first."

less precise probability beliefs should be less willing to take risk.[31] The results in Table 2.7 are consistent with their hypothesis, such that a one-standard deviation higher average FEP is associated with a 20% higher level of risk tolerance.[32] An increase in current FEP relative to the individual's panel average FEP is also associated with a substantial increase in risk tolerance.

This paper focuses on within-person changes and across-person differences in risk tolerance that are systematically related to other observed attributes. Yet, the gamble responses also imply a large amount of residual variation. The model of risk tolerance allows for an individual-specific, time-constant component of risk tolerance that is uncorrelated with the observables. In Table 2.7 the estimated standard deviation of this random individual effect is 0.72 which is large both in absolute terms and relative to the other estimated mean effects. As a comparison, the standard deviation of log risk tolerance that is systematically associated with the rich set of covariates is 0.41. There is even more transitory variation in the gamble responses that is unrelated to the observables. The estimated standard deviation of the response errors is 1.55 and is more than twice the standard deviation of the individual effect. The magnitude of these residuals highlights the scope for further investigation of time-constant survey response errors and transitory preference shocks.

As the first two columns of Table 2.7 reveal, the modelling of the response error variance affects the estimates of risk tolerance. The baseline model in the first column allows the estimated standard deviation of the transitory response errors to vary with the model covariates. The model in the second column instead imposes homoscedasticity. While the qualitative patterns in risk tolerance are largely the same, in many cases, the point estimates on the direct and type effects differ substantial across the two models of response error variance. For example, the standard deviation of men's response error is 12% larger than women's

[31] A common survey response strategy on subjective questions could provide an alternate source of covariation between an individual's gamble and probability responses. To minimize survey time and effort, some individuals may choose the "easy" answer to both questions, that is, 0-50-100 on the probabilities and reject the risky (and computationally intensive) job on the gambles.

[32] Kézdi and Willis (2006) also establish a positive association between actual stock ownership and more precise probability beliefs. The statistical model of risk tolerance that I estimate is observationally equivalent to uncertainty aversion model of Lillard and Willis (2001), but I do not explicitly test their mechanism.

response error, so in the homoscedastic model, the estimated difference in risk tolerance by gender increases to 22% from 14% in the heteroscedastic model.[33] These shifts in the point estimates also reflect the nonlinearity of the maximum-likelihood model.

2.4.5 Measure of Individual Risk Tolerance

The model estimates can also be used to form a proxy for an individual's risk tolerance at a particular point in time. Specifically, I calculate the expected value of log risk tolerance conditional on the individual's observed attributes x_{it} and $\overline{x}_i$ and gamble responses c_i in the panel, such that,

$$(2.15) \qquad \mathrm{E}(\log\theta_{it}|x_{it},\overline{x}_i,c_i) \;=\; x_{it}\beta+\overline{x}_i\lambda+\mathrm{E}(u_i|x_{it},\overline{x}_i,c_{it},...c_{iT})\ .$$

The mean of the random effect u_i conditional on attributes $\overline{x}_i$ is zero, yet an individual's set of gamble responses $c_i=(c_{it},...c_{iT})$ does provide some information on the expected level of this component.[34]

The decomposition of the preference measure into permanent and transitory components is again useful with

$$(2.16) \qquad \mathrm{E}(\log\theta_{it}|x_{it},\overline{x}_i,c_i) \;=\; (x_{it}-\overline{x}_i)\beta+\overline{x}_i(\beta+\lambda)+\mathrm{E}(u_i|x_{it},\overline{x}_i,c_i)$$

where the first term on the right is a transitory component related to changes in the observed attributes of an individual, the second term is a permanent component related to differences across individuals in their observed attributes, and the third term is a permanent component related only to the difference across individuals in their gamble responses. The variance of the systematic within-person changes in risk tolerance (the first term) accounts for only 11% of the total variance in the individual measure of risk tolerance, whereas the variance of the systematic across-person differences (the second term) accounts for 45% of the total variance. Both changes in risk tolerance over time and differences in risk tolerance across

[33]The estimated effects of age and income, not reported here, are also greatly affected by the error variance assumptions. The homoscedastic model estimates a 47% smaller decrease in risk tolerance with age than the baseline model (a direct effect of -1.2% under versus -1.7%). The difference in risk tolerance associated with differences in average income is 50% smaller (0.06% versus 0.09%) and no longer statistically different from zero.

[34]The variance of the conditional expectation of $\log\theta_{it}$ is much smaller than its unconditional variance. See Kimball et al. (2007) for a further discussion of how this diminished variability impacts the use of a proxy based on the conditional expectation.

individuals contribute to the systematic heterogeneity in measured preferences, though the stable differences across individuals are empirically more important. A substantial portion of the between-person variation in the risk tolerance proxy is not related to the observables in the model.

2.5 STOCK OWNERSHIP

The primary reason to study preferences is to better understand behavior, so in this section I use the individual measure of risk tolerance from the gamble responses to analyze the considerable differences in stock ownership across households over the 1990s. As economic theory predicts, there is a strong positive association between the measure of risk tolerance and the holding of risky financial assets. A transitory increase in risk tolerance, as well as a persistently higher level of risk tolerance both raise the marginal probability of actual stock ownership. The measure of risk tolerance also refines the common inference on other determinants of stock ownership, including the effects of gender, education, and wealth. Finally this analysis of stock ownership highlights the usefulness and validity of the risk tolerance proxy.

To study stock ownership, I follow the financial respondents from the original HRS households over the first six waves from 1992 to 2002. The financial respondent is the individual who is most knowledgeable about the finances of the household and who reports on the income and wealth in the survey. In my analysis of stock ownership, I exclude financial respondents who are in households with no financial assets, negative net worth, or no income at any of the six survey waves. This yields a balanced panel of 2,464 financial respondents with 14,784 household-wave observations.[35] In the pooled sample, 46% of the financial respondents own stocks directly.[36] The cross-sectional rate of stock ownership varies in the panel period. Stock ownership increases from 41% of households in the 1992 HRS to 47% of

[35] I follow a financial respondent even if his or her original household dissolves. This structure to the data reflects the fact that I measure risk tolerance at the individual level, but assets are typically held jointly in the household. At any wave, there is only one member of each household in my sample.

[36] The definition of stocks includes financial assets in corporate stocks, mutual funds, or investment funds and excludes stocks held indirectly in IRAs or DC-pensions.

households in the 2000 HRS and then decreases slightly to 45% in the 2002 HRS. Following the same respondents over the panel, 28% never hold stocks, 20% always hold stocks, and 52% change ownership status at least once.

The first column of Table 2.8 presents the estimated marginal effects on the probability of owning stocks for a subset of the model covariates.[37] The results in the first column are similar to the results in numerous studies of household portfolios, for examples, see Guiso et al. (2002). Men are 3 percentage points more likely to own stocks than women, though the effect is not precisely estimated. Higher levels of education and wealth are particularly strong predictors of stock ownership. College graduates are 19 percentage points more likely to own stocks than high school graduates. A 10% higher average wealth across individuals is associated with a 2.9 percentage point higher probability of stock ownership, and a 10% increase in wealth for a particular individual increases the probability of stock ownership by 1.4 percentage points.

The results in the second column of Table 2.8 show how a direct measure of risk tolerance refines the inferences on stock ownership. This model adds two measures of individual's risk tolerance: the average of log risk tolerance across the six survey waves and the deviation between current log risk tolerance and the panel average level. As economic theory predicts, both measures of risk tolerance are positively associated with stock ownership.[38] A 10% higher level of average risk tolerance across individuals is associated with a 1.0 percentage point higher probability of stock ownership. And a 10% increase in an individual's risk tolerance raises the probability of stock ownership by 0.9 percentage points. Both of these effects are statistically and economically significant.[39] The model of risk tolerance estimated in Section 2.4 reveals considerable heterogeneity, so a one-standard difference in risk toler-

[37] The correlated random effects probit of stock ownership estimated in Stata includes all the covariates from the model of risk tolerance (see Appendix Table 2.9), except for the fraction of exact probability responses, job displacements and health conditions, and adds indicator variables for the survey waves. The key exclusion restriction is that FEP does not affect stockholding directly. Its effect on stock ownership is mediated through risk tolerance. The marginal effects are computed at the sample median of the variables with the random effect set to zero.

[38] Other measures of stock ownership, such as the dollar value of stock holding and the share of financial assets held in stocks, produce qualitatively similar results. My results in the panel are consistent with the results of Barsky et al. (1997) in the cross-section.

[39] The asymptotic standard errors in the second column Table 2.8 do not account for the sampling variation in the risk tolerance measures which are generated from the first-step maximum-likelihood estimates. Bootstrap replications on a related, but computationally less intensive model in Kimball et al. (2007) yield only modest increases in the standard errors.

ance corresponds to a 8.2 percentage point difference in the predicted probability of stock ownership — almost one-fifth of the actual ownership rate.

The measure of risk tolerance also refines the association between stock ownership and the other covariates. For example, the variation in risk tolerance absorbs much of the higher probability of stock ownership among men that is estimated in the first model. Likewise the effect of education on stock ownership is partially reduced when the model includes a measure of risk tolerance. Specifically, the estimated marginal effects of a college education and post-graduate education drop by 17% and 35% respectively. These results suggest that differences in risk preference can account for some of the commonly observed association between education and stock ownership. In contrast, Table 2.8 shows that the marginal effect of wealth on stock ownership is unrelated to differences in risk preference. Alternate explanations, such as transaction costs, are needed to explain the strong association between wealth and stock ownership, since there is no evidence of decreasing relative risk aversion. A direct measure of risk tolerance provides an opportunity to explore the mechanisms behind the large differences in stock ownership across households and over time. The strong association between the measure of risk tolerance and actual stock ownership also demonstrates that the hypothetical gambles capture meaningful differences in preferences.

2.6 CONCLUSION

Risk tolerance differs systematically both across individuals and over time. Most of these differences stem from characteristics, such as gender and ethnicity, that are constant over time for a particular individual; however, there are some sources of systematic change in an individual's risk tolerance, such as aging and changes in macroeconomic conditions. Other changes in individual circumstances, including the loss of a job or the end of a marriage, reveal information about individuals' risk tolerance type, not a change in their willingness to take risk.

The fact that risk tolerance differs greatly across individuals but is relatively stable for a particular individual has important consequences for studying risky behavior. The large differences in risk preference across individuals underscore the need for a survey measure of these differences. The relative stability of preferences and the correspondence between this survey measure of risk tolerance and actual risky behavior support our ability to measure risk preference at the individual level. Yet, the apparent noisiness of the hypothetical gamble responses needs to be further explored with higher frequency data and other survey questions, since the "survey response error" may be absorbing short-lived, but behaviorally important preference shocks. Nonetheless, it is clear that economic studies of behavior need to take into account the stable component of risk preference that differs systematically across individuals.

ACKNOWLEDGMENTS

The author thanks Matthew Shapiro, Miles Kimball, Gary Solon, Tyler Shumway, Bob Willis, Dan Benjamin, Chris House, David Laibson, Matthew Rabin, Richard Thaler, and seminar participants at University of Michigan, University of Illinois, Rice, Ohio State University, Wharton, Michigan State University, University of Wisconsin-La Crosse, and the Federal Reserve Bank of Dallas and Board of Governors for helpful discussions. The author gratefully acknowledges the support of a National Institute on Aging Pre-Doctoral Training Fellowship and an Innovation in Social Research Award from the University of Michigan Institute for Social Research. This paper subsumes the draft previously circulated with the title "Does Risk Tolerance Change?"

Table 2.1: Risk Tolerance Response Categories

Response	Downside Risk of Risky Job		Bounds on Risk Tolerance	
Category	Accepted	Rejected	Lower	Upper
1	None	1/10	0	0.13
2	1/10	1/5	0.13	0.27
3	1/5	1/3	0.27	0.50
4	1/3	1/2	0.50	1.00
5	1/2	3/4	1.00	3.27
6	3/4	None	3.27	∞

NOTE: In a series of questions, respondents choose between a job with a certain income and a job with risky income. With equal chances, the risky job will double lifetime income or cut lifetime income by a specific fraction (downside risk). The largest risk accepted and the smallest risk rejected across gambles define a response category. In 1992 there are four categories 1-2, 3, 4, and 5-6. In 1994 and later surveys, the response categories range from 1 to 6. At the lower bound of risk tolerance for a category, an individual with CRRA utility is indifferent between the certain job and a risky job with the largest downside risk accepted. The upper bound similarly follows from the smallest downside risk rejected.

Table 2.2: Responses to Lifetime Income Gambles

Response Category	% by HRS Survey Wave 1992	1994	1998	2000	2002
1	64.7	44.4	39.5	45.0	43.2
2		17.2	18.7	19.4	18.8
3	11.9	13.8	16.2	14.6	15.6
4	10.9	15.0	9.4	8.6	9.9
5	12.5	5.9	9.1	6.8	6.5
6		3.7	7.1	5.6	6.0
Responses	9,647	594	2,502	943	4,939

NOTE: Author's unweighted tabulations from HRS public access data files. The sample includes 12,003 individuals in the 1931 to 1947 birth cohorts. See the text for details on the sample selection. See Table 2.1 for the definition of the response category.

Table 2.3: Attributes at Gamble Response 1992 - 2002

Percent	1992-2002
Male	42.9
Black	14.7
Hispanic	7.5
High School Drop Out	22.0
H.S. Grad / Some College	57.2
College / Post Graduate	20.8
Job Displacement	
Prior to Response	24.7
After to Response	12.9
Health Condition	
Prior to Response	22.0
After to Response	16.8
Married	
Current Status	78.9
Change in Panel	13.5
Mean (Std. Dev.)	
Age	56.9
	(4.5)
Fraction Exact Probability	
Individual Panel Average	0.41
	(0.18)
Current - Panel Average	0.04
	(0.16)
Log of Income	
Individual Panel Average	10.9
	(0.8)
Current - Panel Average	-0.04
	(0.47)
Log of Wealth (Positive)	
Individual Panel Average	11.5
	(2.5)
Current - Panel Average	-0.15
	(0.75)
Responses	18,625

NOTE: Author's unweighted tabulations are from HRS public access data files and Rand HRS (Version F) data set. The sample includes 12,003 individuals. A job displacement is a job ending with a firm closure or layoff. A health condition includes heart disease, stroke, cancer, and lung disease. Fraction exact probability is the fraction of subjective probability questions to which the respondent gave a non-focal answer (not 0, 50, or 100). Wealth is the total household net worth and income is the total income of the respondent and spouse. Both variables are from the RAND HRS data and include imputations.

Table 2.4: Household Income and Wealth

Latent Variable: Log of Risk Tolerance		
Parameter	All Gamble Respondents	Working Household Heads
Direct Effect: β		
Log of Current Income	0.03	0.03
	(0.03)	(0.06)
Log of Positive Current Wealth	0.01	-0.03
	(0.02)	(0.03)
Log of | Negative Current Wealth |	0.03	0.01
	(0.02)	(0.03)
Direct and Type Effects: $\beta + \lambda$		
Log of Average Income	**0.09**	**0.14**
	(0.03)	(0.06)
Log of Positive Average Wealth	0.003	-0.02
	(0.014)	(0.02)
Log of | Negative Average Wealth |	**0.05**	0.01
	(0.03)	(0.04)
Log-likelihood	-23573.5	-10022.8
Number of Respondents	12,003	5,692

NOTE: Asymptotic standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. Income is total earnings, pensions, government transfers, and capital income received by the respondent and spouse in the household. Wealth is total household wealth (including housing, vehicles, businesses, and IRAs) minus all debts. The model in the first column is estimated with all the gamble responses. Appendix Table 2.9 provides the full set of covariates and estimates. The second column only includes gamble responses from household heads who are working.

Table 2.5: Job Displacement and Health Condition

Latent Variable: Log of Risk Tolerance		
Parameter	All Gamble Respondents	Balanced Panel of HRS
Direct Effect: β		
Previous Job Displacement	-0.06	-0.11
	(0.07)	(0.08)
Previous Health Condition	-0.09	**-0.15**
	(0.06)	(0.07)
Type Effect: λ		
Ever Job Displacement	**0.19**	**0.20**
	(0.06)	(0.07)
Ever Health Condition	0.02	0.06
	(0.06)	(0.07)
Log-likelihood	-23573.5	-13426.4
Number of Respondents	12,003	6,591

NOTE: Asymptotic standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. A job displacement is a job ending with a firm closure or layoff. A health condition is heart disease, stroke, cancer, or lung disease. The model in the first column is estimated with all the gamble respondents. Appendix Table 2.9 provides the full set of covariates and estimates. The model in the second column only uses the gamble responses of the individuals who respond to all six HRS waves 1992-2002.

Table 2.6: Age, Cohort, and Time

Latent Variable: Log of Risk Tolerance				
Parameter	Alternate Specifications of Time Effects			
Age	**-0.017**	-0.16	**-0.021**	**-0.021**
	0.008	(0.09)	0.010	0.010
		(0.00)		
1937-1941 Cohorts	**0.16**	**0.17**	0.14	0.14
	(0.06)	(0.07)	(0.07)	(0.07)
1942-1947 Cohorts	0.16	0.16	0.10	0.10
	(0.10)	(0.11)	(0.12)	(0.12)
		(0.00)		
Consumer Sentiment	**0.009**	**0.006**		**0.007**
	(0.002)	(0.003)		(0.004)
ICS Six Months Ago		0.004		
		(0.003)		
ICS One Year Ago		-0.001		
		(0.003)		
1994 HRS			**0.27**	**0.19**
			(0.08)	(0.09)
1998 HRS			**0.37**	0.19
			(0.08)	(0.11)
2000 HRS			**0.32**	0.12
			(0.11)	(0.14)
2002 HRS			**0.24**	0.17
			(0.11)	(0.11)
1992/1994 Version	-0.08	-0.05		
	(0.09)	(0.12)		
Log-likelihood	-23573.5	-23571.5	-23571.2	-23569.0
Parameters	55	59	59	61

NOTE: Asymptotic standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. The sample includes 12,003 individuals. The first column is the baseline specification of the model, see Appendix Table 2.9 for the full set of covariates and estimates. The 1931-1936 birth cohort is the omitted cohort group. Consumer Sentiment is the value of the University of Michigan Index of Consumer Sentiment (ICS) in the month of an individual's gamble response. Over the months with HRS gamble responses, the ICS from the Survey of Consumers ranges from a low of 73.3 in October 1992 to high of 111.3 in February 2000. A gamble response on the 1992 HRS survey is the omitted wave control. The "new job" version of the income gamble question is asked in the 1992 and 1994 waves of the HRS.

Table 2.7: Individual Attributes

Latent Variable: Log of Risk Tolerance		
	Model Allows for Heteroscedastic Errors	
Parameter	Yes	No
Direct and Type Effects: $\beta + \lambda$		
Male	**0.14**	**0.22**
	(0.04)	(0.03)
Black	**-0.28**	**-0.12**
	(0.06)	(0.05)
Hispanic	-0.03	0.05
	(0.08)	(0.06)
High School Drop Out	0.02	**0.09**
	(0.06)	(0.04)
Some College	**0.17**	**0.19**
	(0.05)	(0.04)
College Graduate	**0.22**	**0.25**
	(0.06)	(0.06)
Post Graduate	**0.32**	**0.40**
	(0.06)	(0.06)
Direct Effect: β		
Currently Married	0.11	0.10
	(0.09)	(0.08)
Fraction Exact Probability	**0.82**	**0.52**
	(0.10)	(0.09)
Type Effect: λ		
Proportion of Years Married	**-0.27**	**-0.23**
	(0.10)	(0.09)
Average FEP Across Waves	**0.27**	-0.05
	(0.14)	(0.12)
Std. Dev. of Individual Effect : σ_u	**0.72**	**0.77**
	(0.03)	(0.03)
Std. Dev. of Response Error: σ_e	**1.55**	**1.50**
	(0.01)	(0.02)
Log-likelihood	-23573.5	-23801.3
Parameters	55	29

NOTE: Asymptotic standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. The sample includes 12,003 individuals. Appendix Table 2.9 provides the full set of covariates and estimates for the baseline model in the first column. The model in the second column imposes homoscedasticity on the response errors. Fraction exact probability (FEP) is the fraction of the subjection probability questions in the survey to which an individual gives a non-focal response (not 0, 50, or 100). The covariates under the type effects are an individual's average over the panel period.

Table 2.8: Decision to Own Stocks

Dependent Variable: Indicator of Stock Ownership		
Subset of Parameters	Marginal Effect on Probability	
Log Risk Tolerance		
Individual Panel Average		**0.10**
		(0.03)
Current - Panel Average		**0.09**
		(0.04)
Male	0.03	0.01
	(0.03)	(0.03)
High School Drop Out	**-0.15**	**-0.15**
	(0.03)	(0.03)
Some College	0.06	0.04
	(0.03)	(0.03)
College Graduate	**0.19**	**0.16**
	(0.04)	(0.04)
Post Graduate	**0.11**	0.07
	(0.04)	(0.04)
Log of Current Wealth	**0.14**	**0.15**
	(0.01)	(0.01)
Log of Average Wealth	**0.15**	**0.16**
	(0.02)	(0.02)
Predicted Probability	0.31	0.34
Log-Likelihood	-6904.94	-6897.3

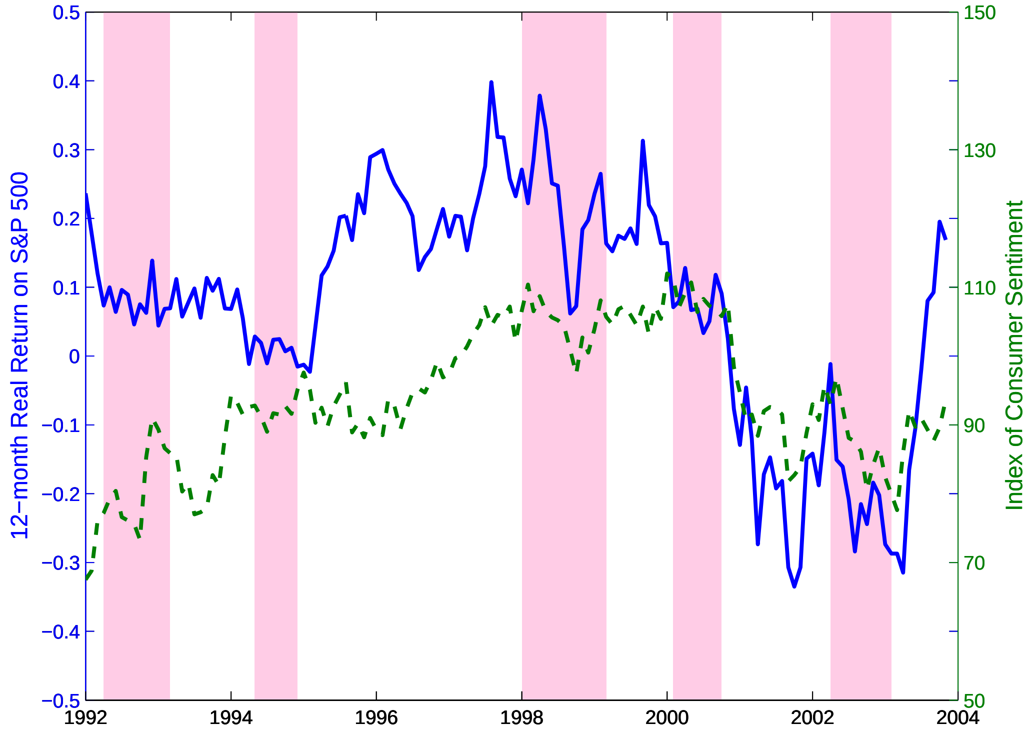
NOTE: Asymptotic standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. The correlated random effects probit is estimated on a balanced panel with 2,464 financial respondents and 14,784 total observations from the 1992 to 2002 HRS. The model of stock ownership includes all the covariates from the model of risk tolerance (see Appendix Table 2.9) except for the fraction of exact probability responses, job displacements and health conditions. The stock ownership model adds indicator variables for the survey waves. The marginal effect of a variable on the probability to own stocks is computed at the median values of the variables with the random effect equal to 0.

Appendix Table 2.9: Maximum-Likelihood Estimates of Log Risk Tolerance

Latent Variable: Log of Noisy Risk Tolerance: ξ_{it}				
	Mean Effect			Std. Dev.
Variable	Direct	Type	Composite	Effect
Constant			**-3.16**	**1.68**
			(0.71)	(0.47)
Male			**0.15**	**0.11**
			(0.03)	(0.02)
Black			**-0.28**	**0.19**
			(0.06)	(0.03)
Hispanic			-0.04	**0.14**
			(0.08)	(0.04)
1937-1941 Cohorts			**0.17**	-0.01
			(0.06)	(0.04)
1942-1947 Cohorts			0.16	0.01
			(0.10)	(0.07)
Drop Out			0.02	**0.07**
			(0.05)	(0.03)
Some College			**0.18**	0.03
			(0.05)	(0.03)
College Graduate			**0.23**	-0.01
			(0.06)	(0.04)
Post College			**0.34**	0.03
			(0.05)	(0.04)
Index Consumer Sentiment / 10	**0.09**			**-0.05**
	(0.02)			(0.02)
Current Age / 10	**-0.17**			0.01
	(0.08)			(0.05)
Currently Married	**0.18**			-0.07
	(0.09)			(0.06)
Fraction Exact Probability	**0.78**			**-0.44**
	(0.10)			(0.07)
Previous Job Displacement	-0.06			0.003
	(0.06)			(0.05)
Previous Health Condition	-0.09			-0.05
	(0.06)			(0.05)
Log (Current + Wealth) / 10	0.11			**-0.21**
	(0.16)			(0.10)
Log (| Current − Wealth |) / 10	0.34			-0.11
	(0.19)			(0.12)
Log (Current Income) / 10	0.08			-0.06
	(0.17)			(0.10)
Proportion of Years Married		**-0.35**		0.06
		(0.10)		(0.07)
Panel Average FEP		**0.32**		**-0.57**
		(0.13)		(0.09)
Ever Job Displacement		**0.20**		0.02
		(0.06)		(0.05)
Ever Health Condition		0.01		0.03
		(0.06)		(0.04)
Log (Average + Wealth) / 10		-0.02		**0.28**
		(0.20)		(0.12)
Log (| Average − Wealth |) / 10		0.16		**0.38**
		(0.27)		(0.15)
Log (Average Income) / 10		0.60		**-0.48**
		(0.34)		(0.20)
"New Job" Version			-0.06	-0.09
			(0.09)	(0.06)

NOTE: The estimated standard deviation of the unpredictable persistent component is 0.72.

Figure 2.1: Stock Market Returns and Consumer Sentiment, 1992 - 2004



NOTE: The solid line is the total annual return from the S&P 500 Total Return Index (including dividends) over the previous 12 months. The monthly value of the S&P 500 Index is the closing value on the last business day of the month. The index from Global Financial Data is adjusted for dividends and splits. The CPI-U removes general price inflation from the return. The dashed line is the current monthly value of the Index of Consumer Sentiment from the University of Michigan Survey of Consumers. The shaded areas denote months in which the HRS fielded the income gambles. These interview months for the five waves are 4/1992 to 3/1993, 5/1994 to 12/1994, 1/1998 to 3/1999, 2/2000 to 11/2000, and 4/2002 to 2/2003.

CHAPTER III

Imputing Risk Tolerance from Survey Responses

3.1 INTRODUCTION

Choices with uncertain outcomes, such as financial investments, career paths, and health practices, are numerous and important to welfare. Empirical studies of these behaviors often suffer from a common weakness — the inability to take into account heterogeneity in preferences. In this paper, we develop a quantitative proxy for risk tolerance based on responses from a large-scale survey to account for this heterogeneity. We then use the proxy to study asset allocation.

Our measurement of risk tolerance is based on individuals' responses to questions about hypothetical risky choices. In particular, we ask them to choose between a job with a certain lifetime income and a job with a random, but higher mean lifetime income. We show how to translate these ordinal responses into a cardinal proxy for risk tolerance. To construct this proxy and use it to study behavior, we confront a number of issues. First, the survey responses about gambles over lifetime income imply a range instead of a point value for the unobserved cardinal preference parameter. Second, the survey responses are likely to be subject to measurement error. We develop a statistical model addressing both issues. Multiple responses from some individuals and refinements to the survey questions isolate the true variation in risk preferences. With the maximum-likelihood estimates, we compute the proxy value — the expectation of risk tolerance conditional on survey responses — for each individual. Based on a small set of survey questions, the proxy may not fully capture the systematic variation in risk preferences. This induces a nonstandard errors-in-variables problem in regression estimates that use the proxy as an explanatory variable. We provide an estimator using the proxy that is consistent despite errors in variables.

The plan of the paper is as follows. Section 3.2 discusses the survey questions on lifetime income gambles and the distribution of responses in the Health and Retirement Study. Section 3.3 shows how to construct the cardinal proxy for risk tolerance from these survey responses and Section 3.4 addresses the presence of survey response error. Researchers will be able to use such a proxy as an explanatory variable in studying a wide range of behaviors. In Section 3.5, we show how to estimate consistently the effect of the preference parameter on behavior. Section 3.6 applies these procedures to study the asset allocation decision. Our results show that our improved measure of risk preference significantly alters the estimated effects of risk tolerance and other observable characteristics on asset allocation. The final section offers conclusions.

3.2 SURVEYING RISK PREFERENCES

The Health and Retirement Study (HRS) is a large-scale, biennial survey, which began in 1992 with a representative sample of individuals between ages 51 to 61 and their spouses. In addition to detailed financial and demographic information, the study elicits risk preferences using a battery of questions developed by Barsky, Juster, Kimball, and Shapiro (1997). The Panel Study of Income Dynamics, National Longitudinal Study, Surveys of Consumers, Dutch CentERpanel, and Chilean Social Security Survey have also fielded these gambles over lifetime income. In hypothetical scenarios, respondents choose between a certain job and a risky job. With equal chances, the risky job will double lifetime income or cut lifetime income by a specific fraction (or downside risk). Varying the downside risk on the new job in subsequent questions refines the measure of risk preferences.

Specifically, in 1992 the HRS poses the following scenario:

> Suppose that you are the only income earner in the family, and you have a good job guaranteed to give you your current (family) income every year for life. You are

> given the opportunity to take a new and equally good job, with a 50-50 chance it will double your (family) income and a 50-50 chance that it will cut your (family) income by a third. Would you take the new job?

Individuals accepting this new, risky job then consider one with a higher downside risk:

> Suppose the chances were 50-50 that it would double your (family) income, and 50-50 that it would cut it in half. Would you still take the new job?

Those initially declining the new job consider one with a lower downside risk:

> Suppose the chances were 50-50 that it would double your (family) income and 50-50 that it would cut it by 20 percent. Would you then take the new job?

These two responses order individuals in four categories: unwilling to risk any income cuts, willing to risk at most a one-third cut, willing to risk a one-third to a one-half cut, and willing to risk at least a one-half cut. In 1994 a randomly selected sub-sample answered the questions again. In 1994 and later implementations, there were additional questions about the willingness to accept one-tenth and three-quarter cuts. With these additional gambles, there are six distinct response categories. The first two columns of Table 3.1 relate these response categories to the downside risks of the new jobs. In Section 3.3, we will discuss the last two columns of Table 3.1 that relate the response categories to the preference parameter.

In general, the gambles over lifetime income reveal a low tolerance for risk. As reported in Table 3.2, almost two-thirds of the respondents in 1992 are in the least risk tolerant category 1-2. The remaining one-third of respondents divide almost equally among the other three categories. The distribution of risk categories in 1994 follows a similar pattern. Over 60% of respondents fall in categories 1 or 2 with most choosing the least risk tolerant category 1.

Repeated observations from some individuals will be central to our statistical strategy for separating signal from noise in the survey responses. Among the 693 respondents who answer in the gambles in both the HRS 1992 and 1994, the simple correlation of the response categories across the two waves is 0.27 and almost half switch response categories. Altogether, the survey responses suggest substantial and persistent differences in risk preferences across individuals, but also large changes in responses within individuals across surveys.

The 1998 HRS introduced a new situational frame for the income gambles to remove the potential for status-quo bias. In the original question, individuals choose between their *current* certain job and a *new* risky job. An unwillingness to switch jobs may reflect their aversion to the risky income at the new job or their desire to maintain the status quo. Status quo bias appears to be a common feature in many settings (Samuelson and Zeckhauser 1988). In the presence of status quo bias, estimates from the original question would understate individuals' true risk tolerance. Using a pilot study of undergraduates, Barsky et al. (1997) estimate average risk tolerance to be 24% lower with responses to the original question than with responses to an alternate question free of status quo bias. In 1998, 2000, and 2002, the HRS fielded a status-quo-bias-free question, in which individuals choose between two new jobs. The question wording is

> Suppose that you are the only income earner in the family. Your doctor recommends that you move because of allergies, and you have to choose between two possible jobs.
>
> The first would guarantee your current total family income for life. The second is possibly better paying, but the income is also less certain. There is a 50-50 chance the second job would double your total lifetime income and a 50-50 chance that it would cut it by a third. Which job would you take — the first job or the second job?

As in the original version, follow-up questions vary the downside risk of the second job and responses assign individuals to one of six categories. Starting in 2000, the job-related gambles are targeted to individuals less than age 65. The final three columns of Table 3.2 shows the responses to the status-quo-bias-free question. In this paper, we restrict the sample to original respondents of the HRS who answered the gambles in 1992 or 1994. The respondents in 1998 to the new question do appear more risk tolerant with only 56.9% in category 1-2 compared to 64.6% in 1992 and 61.5% in 1994. This difference disappears in the last two survey waves. Nonetheless, variation in the question wording allows us to estimate the status-quo bias and question-specific responses errors.

This approach to measuring risk preference from hypothetical gambles in the HRS differs fundamentally from earlier survey measurement of attitudes toward risk. Other surveys commonly use categorical responses with vague quantifiers to probe risk preferences. For example, beginning in 1983, the Survey of Consumer Finances (SCF) asks respondents:

> Which of the statements comes closest to the amount of financial risk that you and your (spouse/partner) are willing to take when you save or make investments?
>
> 1. take substantial financial risks expecting to earn substantial returns
> 2. take above average financial risks expecting to earn above average returns
> 3. take average financial risks expecting to earn average returns
> 4. not willing to take any financial risks

While intended to order respondents by their risk tolerance, the subjective wording may generate uninterpretable variation. Since individuals must define "substantial," "above average," and "average" financial risks and returns, we cannot quantify differences across responses. In contrast, the income gambles on the HRS supply objective boundaries between risk categories. In the next section, we use economic theory to map survey responses to a cardinal proxy for risk tolerance.

Using the cardinal proxy has several advantages. First, it provides a unidimensional, quantitative measure of risk tolerance that allows meaningful interpersonal comparisons. Second, in many settings, such as the demand for risky assets that we study in Section 3.6, economic theory makes predictions that link risk preference parameters quantitatively to economic decisions. Third, by having a quantitative measure we can correct for the measurement error inevitable with proxies based on survey responses.

3.3 CONSTRUCTING A CARDINAL PROXY

Expected utility theory provides a cardinal metric for risk preference — the coefficient of relative risk tolerance. Denote an individual's concave utility function over original lifetime income as $U(W)$. Faced with 50-50 gambles of doubling lifetime income or cutting it by various fractions π, an individual should accept the risky job when its expected utility exceeds the utility from the certain job — that is, if

$$0.5U(2W) + 0.5U((1-\pi)W) \;\; \geq \;\; U(W). \tag{3.1}$$

The greater the curvature of U, the smaller the downside risk π an individual will accept. Associating gamble responses more tightly with underlying risk tolerance requires a parametric utility function.

We assume that constant relative risk aversion (CRRA) well approximates individuals' utility over lifetime income

$$U(W) \;\; = \;\; \frac{W^{1-1/\theta}}{1-1/\theta} \tag{3.2}$$

where the coefficient of relative risk tolerance θ may differ across individuals. This form implies that relative risk tolerance, $\theta = -U'/WU''$ (Pratt 1964), is constant across all values of lifetime income for a given individual. Analysis of the gamble responses with household income and wealth supports this utility specification (Sahm 2007). We focus on relative risk tolerance θ rather than relative risk aversion $1/\theta$ because relative risk tolerance is linearly related to demand for risky financial assets (Breeden 1979). While the survey does not directly measure risk tolerance, the responses to the income gambles with this utility function establish boundaries on the underlying preference parameter.

To illustrate how to bound risk tolerance, consider individuals in response category 3. By accepting the risky job when the downside risk is one-fifth, but declining when the downside risk is one-third, these individuals reveal risk tolerance between 0.27 and 0.50. Each bound for this category equates the expected utility of a new risky job and the current certain job:

$$\underline{\theta}_3 = 0.27 \iff 0.5\frac{2^{1-1/\underline{\theta}_3}}{1-1/\underline{\theta}_3} + 0.5\frac{(1-1/5)^{1-1/\underline{\theta}_3}}{1-1/\underline{\theta}_3} = \frac{1^{1-1/\underline{\theta}_3}}{1-1/\underline{\theta}_3} \tag{3.3}$$

$$\overline{\theta}_3 = 0.50 \iff 0.5\frac{2^{1-1/\overline{\theta}_3}}{1-1/\overline{\theta}_3} + 0.5\frac{(1-1/3)^{1-1/\overline{\theta}_3}}{1-1/\overline{\theta}_3} = \frac{1^{1-1/\overline{\theta}_3}}{1-1/\overline{\theta}_3} \; . \tag{3.4}$$

Substituting the largest downside risk accepted and smallest risk rejected from Table 3.1, we similarly determine the lower and upper bounds for the other categories. The last two columns of Table 3.1 report the bounds for each response category. The categories exhaust the possible range of risk tolerance.

In the next section, we consider a more general model that accounts for measurement error and other features of the question. To illustrate how we map the discrete responses into a continuous distribution, assume that true risk tolerance follows a log-normal distribution,

$$\log \theta \equiv x \sim N(\mu, \sigma_x^2) \ . \tag{3.5}$$

The lognormal functional form has several advantages. First, it imposes the restriction that relative risk tolerance is nonnegative. Second, it is parsimonious and computationally simple. Third, we are able to use the moment generating function of the normal to calculate analytically the unconditional and conditional expectations of $\theta = \exp(x)$. Finally, the lognormal appears to fit the data well. It can capture the fact that the modal value of relative risk tolerance is close to zero but that a substantial fraction of individuals have higher risk tolerance.

We use standard maximum likelihood methods to estimate the mean μ and variance σ_x^2 of log risk tolerance in the population. Consider first a case in which we observe one response category c for each individual. The probability of being in category j is

$$\begin{aligned} \mathrm{P}(c = j) &= \mathrm{P}(\log \underline{\theta}_j < x < \log \overline{\theta}_j) = \\ &= \Phi\left((\log \overline{\theta}_j - \mu)/\sigma_x\right) - \Phi\left((\log \underline{\theta}_j - \mu)/\sigma_x\right) \end{aligned} \tag{3.6}$$

where $\Phi(\cdot)$ is the cumulative normal distribution function. Maximizing the sample log-likelihood of the individuals' first gamble response, yields a mean log risk tolerance of -1.98 and a standard deviation of 1.76 as reported in the first column of Table 3.3. These parameters are precisely estimated: both have an asymptotic standard error of 0.03. For the maximum-likelihood estimation, we use the modified method of scoring where the sample average of the outer product of the score function approximates the information matrix.

For many applications, it is valuable to assign a numerical risk tolerance proxy for each individual conditional on his or her survey responses. Using the estimated population parameters, we can impute log risk tolerance conditional on a survey response in category j as

$$E(\log\theta|c=j) \quad = \quad \mu+\sigma_x\frac{\phi\left((\log\underline{\theta}_j-\mu)/\sigma_x\right)-\phi\left((\log\overline{\theta}_j-\mu)/\sigma_x\right)}{\Phi\left((\log\overline{\theta}_j-\mu)/\sigma_x\right)-\Phi\left((\log\underline{\theta}_j-\mu)/\sigma_x\right)} \tag{3.7}$$

where $\phi(\cdot)$ is the standard normal density function. Alternately, from the moment generating function we can impute risk tolerance as

$$E(\theta|c{=}j)=\exp\!\left(\mu+\frac{\sigma_x^2}{2}\right)\frac{\Phi\big((\log\overline{\theta}_j-\mu-\sigma_x^2)/\sigma_x\big)-\Phi\big((\log\underline{\theta}_j-\mu-\sigma_x^2)/\sigma_x\big)}{\Phi\left((\log\overline{\theta}_j-\mu)/\sigma_x\right)-\Phi\left((\log\underline{\theta}_j-\mu)/\sigma_x\right)}\ . \tag{3.8}$$

Given the parameter estimates, the proxy, $h=E(\theta|c)$, has four values, 0.083, 0.367, 0.706, and 3.687 for individuals in response categories 1-2, 3, 4, and 5-6. Unlike ordinal rankings, this proxy quantifies the average difference in log risk tolerance across the risk categories.

3.4 ADDRESSING SURVEY RESPONSE ERROR

Responses to hypothetical income gambles likely provide a noisy signal of true risk tolerance. Thus the risk tolerance proxy from the previous section is also error-prone. Statistical procedures that use the risk tolerance proxy will be subject to errors-in-variables problems. In particular, using the proxy as an explanatory variable in a regression will lead to attenuation biases and inconsistent coefficient estimates. Since a key aim of including the risk questions on large-scale surveys is to provide researchers with a means to control for heterogeneity in preferences, it is critical to address and correct for the consequences of survey response error.

That some individuals give multiple responses to the risk tolerance questions provides a lever for quantifying survey response error. By making the structural assumption that preferences are immutable, we attribute the common component in an individual's answers to true preference and the changes to response error. Recall that $x=\log(\theta)$ is the individual's true preference parameter. With two versions of the gamble question, we also incorporate a question-specific persistent response error. The survey response error in wave w to question type q is a normal disturbance ϵ_{qw} added to x that leads the individual to choose the gamble response category corresponding to the sum ξ_{qw}. The error ϵ_{qw} can be interpreted either as an individual's misperception of his or her risk tolerance or an error the individual makes in calculating the bounds $(\overline{\theta_j}, \underline{\theta_j})$ that map preferences into the gambles. Hence

$$\xi_{qw} = x + \epsilon_{qw} = x + b_q + \kappa_q + e_{qw} \tag{3.9}$$

where b_q is a common bias across individuals of question type q, κ_q is the individual's persistent response error for question type q, and e_{qw} is the individual's transitory response error for a particular wave w and question type q. The components are distributed as $\xi_{qw} \sim N(\mu + b_q, \sigma_q^2)$, $\kappa_q \sim N(0, \sigma_{\kappa q}^2)$, and $e_{qw} \sim N(0, \sigma_{eq}^2)$ with $\sigma_q^2 = \sigma_x^2 + \sigma_{\kappa q}^2 + \sigma_{eq}^2$. The covariance in responses across waves for different question types depends only on the variance of true risk tolerance. For the same question type, the variance of the persistent error also affects the covariance across waves. We assume that the survey response error is a purely random — or "classical" — measurement error. Specifically, the response error ϵ_{qw} is independent of an individual's true risk tolerance and any other attributes.

We analyze the two question types, the original question o and the status-quo-bias-free question f, so $q \in \{o, f\}$. In each wave, only one question type is asked. We assume that the new version is not subject to status quo bias on average, so $b_f = 0$ and $\xi_{fw} \sim N(\mu, \sigma_f^2)$. Identification of the parameters requires that at least some individuals answer the gambles more than once and some of the multiple responders answer the same question type more than once. Of the 11,616 individuals in our sample, all answer the original question at least once and 4,244 individuals answer a status-quo-bias-free question. There are 693 individuals who answer the original question twice. For the bias-free question, 471 individuals answer in two surveys and 278 in three surveys.

In Section 3.3, we discuss how an individual with true log risk tolerance x will be assigned to a category by responses to the survey questions. Survey response error can move the individual into a different category from wave to wave and affects assignment to response categories even for those who answer only in one wave. For individuals who respond in only one wave, the likelihood of category j is

$$P(c_w = j) \quad = \quad \Phi\left(\frac{\log \overline{\theta}_j - \mu - b_q}{\sigma_q}\right) - \Phi\left(\frac{\log \underline{\theta}_j - \mu - b_q}{\sigma_q}\right). \tag{3.10}$$

This likelihood depends on the variance of error-prone risk tolerance, σ_q^2, not that of true risk tolerance, σ_x^2. Obviously, if all individuals answered in only one wave to one question type, the problem is under-identified.

For those answering the income gambles in both waves, the probability of observing category j in wave w and category k in wave w' is

$$\begin{aligned} &P(c_w = j, c_{w'} = k) = \\ &= \overrightarrow{\Phi}\left(\frac{\log \overline{\theta}_j - \mu - b_q}{\sigma_q}, \frac{\log \overline{\theta}_k - \mu - b_{q'}}{\sigma_{q'}}, \rho\right) + \overrightarrow{\Phi}\left(\frac{\log \underline{\theta}_j - \mu - b_q}{\sigma_q}, \frac{\log \underline{\theta}_k - \mu - b_{q'}}{\sigma_{q'}}, \rho\right) \\ &-\overrightarrow{\Phi}\left(\frac{\log \overline{\theta}_j - \mu - b_q}{\sigma_q}, \frac{\log \underline{\theta}_k - \mu - b_{q'}}{\sigma_{q'}}, \rho\right) - \overrightarrow{\Phi}\left(\frac{\log \underline{\theta}_j - \mu - b_q}{\sigma_q}, \frac{\log \overline{\theta}_k - \mu - b_{q'}}{\sigma_q}, \rho\right) \end{aligned} \tag{3.11}$$

where $\overrightarrow{\Phi}(\cdot)$ is the bivariate normal cumulative distribution function. When the question type is the same, that is, $q = q'$, the correlation, ρ, between the variables ξ_{qw} and $\xi_{qw'}$ is the fraction $(\sigma_x^2 + \sigma_{kq}^2)/\sigma_q^2$ of the total variance of the error-prone variable due to true log relative risk tolerance plus the question-specific persistent response error. When the question types differ, that is, $q \neq q'$, the correlation is $\sigma_x^2/\sigma_q\sigma_{q'}$ where the covariance depends only on the variation in true log relative risk tolerance. Unlike the typical multiple indicator solution to the errors-in-variables problem, identification here does not require repeat observations from all individuals in the sample.

Maximizing the sample log-likelihood with respect to μ, σ_x, $\sigma_{\kappa o}$, $\sigma_{\kappa f}$, σ_{eo}, and σ_{ef} yields consistent estimates of the parameters. The second column of Table 3.3 reports the estimates. The estimated mean of log risk tolerance -1.84 is somewhat higher in this model with multiple gamble responses and question-specific response errors. The original question type is associated with an 11% lower reported risk tolerance. While this status quo bias is relatively modest, it is statistically different from zero. A more substantial shift occurs in the estimated variation of true log risk tolerance, as the estimate of the standard deviation falls to 0.73

from 1.76. Most of this decline is from modeling transitory response error using multiple gamble responses of some individuals. The modeling of question-specific persistent response error also lowers the estimated heterogeneity in true preferences somewhat. Together this implies a much lower estimate of mean risk tolerance in the population: 0.21 instead of 0.65. The variability from response error greatly exceeds that from true risk tolerance. This finding highlights the limited test-retest reliability of the gambles and the need for multiple responses from some individuals. Nonetheless, the income gambles still convey much useful information on preferences as the application in Section 3.6 validates.

Ignoring survey response error overstates the heterogeneity in risk preferences. As noted, this causes an upward bias in estimated average risk tolerance. This effect is not dependent on the lognormal specification. Given the nonnegativity of risk tolerance, noise will in general shift the mean of the distribution of $\exp(\xi)$ to the right. Figure 3.1 illustrates the effects of response error. The solid line is the empirical distribution of the discrete responses in 1992 from Table 3.2 using the bounds $(\underline{\theta_j}, \overline{\theta_j})$ in Table 3.1. The solid curve is the fitted lognormal distribution of true risk tolerance $\theta = \exp(x)$. The dashed curve is the fitted lognormal distribution of the true parameter plus noise, $\exp(x + \epsilon)$. The figure shows how the distribution of the true parameter moves mass away from the extremes relative to the distribution that includes noise from response errors.

Table 3.4 summarizes additional features of the estimated distribution of true risk preferences based on the parameter estimates in the second column of Table 3.3. The first column shows the distribution of log risk tolerance. The second column shows the distribution of the level of risk tolerance. The estimated mode of 0.094 indicates that the bulk of respondents have very low risk tolerance. Yet, there are enough respondents with relatively high risk tolerance to pull the mean substantially above the mode. About 25% of respondents are estimated to have risk tolerance greater than or equal to 0.259, and about 10% have risk tolerance greater than 0.402. Yet, virtually no respondents have risk tolerance as high as one (logarithmic utility).

For many applications — notably demand for risky assets — relative risk tolerance θ is the relevant preference parameter (Breeden 1979, Barsky et al. 1997). But in other applications, such as the strength of the precautionary saving motive, its reciprocal $1/\theta$, relative risk aversion, would be the parameter of interest (Carroll and Kimball 2007). When preferences are heterogeneous across individuals, the reciprocal of average relative risk tolerance is not equal to the average of its reciprocal. The last column of Table 3.4 gives the parameters and fractiles of the distribution of relative risk aversion. For our parameter estimates, average relative risk tolerance is 0.206. The estimated average of relative risk aversion is 8.2, which is far greater than $1/0.206 = 4.9$. This difference between the expectation of the reciprocal and the reciprocal of the expectation is a powerful example of Jensen's inequality. Jensen's inequality gets its bite in this application from the substantial heterogeneity in preferences, the concavity of the $1/\theta$ function, and the concentrated mass of the probability density near zero, where the function $1/\theta$ is most curved.

Many researchers will want to impute risk tolerance for individuals. As our proxy for individual risk preference, we calculate the expected risk tolerance conditional on an individual's responses, using the estimated distributional parameters of our statistical model. The formula is similar to equation (3.8) in Section 3.3 except that it now accounts for question-specific response error and multiple responses to the gamble questions. Table 3.5 reports the proxy values of risk tolerance, as well as of log risk tolerance and risk aversion, for respondents to one status-quo-bias-free question. The proxy of risk tolerance for response category 1 (reject job with one-tenth downside risk) is 0.153. The range of relative risk tolerance corresponding to those preferences is from 0 to 0.13. (See Table 3.1.) Hence, the proxy value for this response lies slightly higher than the range. For risk category 2, the proxy of 0.203 lies near the center of the range from 0.13 to 0.27. With the more risk tolerant response categories, the proxy values are substantially lower than the range. For example, category 5 (accept a job with one-third downside risk but reject a job with one-half downside risk), the proxy of 0.301 lies far below the low end of the range from 1.0 to 3.7. The proxy values of log risk tolerance and risk aversion follow a similar pattern, as do the proxies from a response to the original question type. Hence, correcting for response error shifts the proxy toward the unconditional mean. Yet, substantial heterogeneity and meaningful quantitative differences remain even after this correction.

For those answering in multiple waves, we use all their responses to sharpen the estimate of their relative risk tolerance. These additional responses greatly widen the range of proxy values. The lowest imputed value of risk tolerance in our sample is 0.087 and the highest value is 0.732. When individuals give different responses across waves, we adjust the proxy values accordingly. Table 3.5 contains only a small subset of the 370 unique proxy values observed in this sample. For researchers who wish to make imputations based on our parameter values for any possible response to the HRS questions, we provide a spreadsheet of all possible values of risk tolerance and risk aversion online (http://www.umich.edu/~shapiro/data/risk_preference).

3.5 STUDYING BEHAVIOR WITH THE PROXY

A major application of our proxy for risk tolerance is its use as a regressor to control for heterogeneity in preferences when studying a wide range of behaviors. The proxy is the conditional expectation of true risk tolerance. Hence, the deviation of the proxy from the true variable $u = \theta - h$ is not a classical measurement error. In particular, the deviation is correlated with the true variable, not the proxy. In this section, we discuss the non-standard errors-in-variables problem that arises from use of the proxy and present an estimator that addresses this problem.

To study the effects of risk tolerance and other regressors on behavior, consider a model

$$y = \theta\delta_\theta + z\delta_z + \nu \tag{3.12}$$

where θ is true risk tolerance and z is a $1 \times K$ vector of observables that also affect the behavior of interest y. To simplify later analysis, all variables are expressed as deviations from their means. We make the assumptions that, conditional on the regressors, the population error is mean zero, $E(\nu|\theta, z) = 0$, and that the expected outer product matrix of (θ, z) has full rank. If we observed true risk tolerance and the other regressors, OLS would consistently estimate the population parameters, $\delta = (\delta_\theta, \delta_z')'$.

Now consider the use of the proxy. Substituting the proxy $h = E(\theta|c)$ in (3.12), we have

$$y = h\delta_\theta + z\delta_z + \eta \tag{3.13}$$

where

$$\eta = u\delta_\theta + \nu \; . \tag{3.14}$$

The composite error term η includes an expectation error $u = \theta - h$ and the structural error term ν. Unlike a classical measurement error, the deviation u of the proxy from the true variable is uncorrelated with the proxy h and correlated with the true variable θ. This implies that in a univariate linear regression of a dependent variable y on only the proxy h, there is no attenuation bias and the OLS coefficient is consistent.

In a multivariate setting, the OLS estimator using the proxy is unlikely to provide consistent estimates of the population parameters, $\delta = (\delta_\theta, \delta_z')'$. The proxy of risk tolerance $h = E(\theta|c)$ only conditions on an individual's gamble response categories, so regressors z that are correlated with true risk tolerance θ would also correlate with the expectation error u. For example, men may be more risk tolerant than women. Then gender would be correlated with the expectation error. Using the proxy with a standard set of demographic regressors, the OLS coefficient estimate for men would mix the direct effects of gender with the indirect effects of risk tolerance. A more general statement of the problem is that

$$E(z'h) \neq E(z'\theta) \; . \tag{3.15}$$

The lack of equality in (3.15) arises because of the correlation between the proxy's expectation error u and the regressors z, which also implies that OLS is inconsistent.

We have enough structure on the problem to derive moment conditions that will allow for a consistent estimator using the proxy. The assumption of purely random response error and the properties of conditional expectations imply that the proxy is uncorrelated with both the structural error term ν and the expectation error u. This yields the following moment condition for the proxy:

$$E(h\eta) \quad = \quad E(hu)\delta_\theta + E(h\nu) = 0 \ . \tag{3.16}$$

To formulate a moment condition for the other observables, we assume that the conditional expectation of each observable z_k in the vector z is linear in risk tolerance, such that

$$z_k \quad = \quad \theta\beta_k + \zeta \tag{3.17}$$

where $E(\zeta|\theta) = 0$ and $\beta_k = E(\theta^2)^{-1}E(\theta z_k)$. The linear specification serves as a good approximation and could be extended to a risk tolerance vector that includes higher order terms. With purely random response error, ζ is independent of the response error ϵ, which together with θ determines the proxy h. This implies that $E(h\zeta) = 0$. By definition, the proxy h is also uncorrelated with the expectation error $u = \theta - h$. Substituting the proxy in (3.17), we have

$$z_k \quad = \quad h\beta_k + u\beta_k + \zeta \tag{3.18}$$

so the regression of z_k on the proxy h consistently estimates β_k, that is, $\beta_k = E(\theta^2)^{-1}E(\theta z_k) = E(h^2)^{-1}E(hz_k)$. We define the true-to-proxy variance ratio as

$$\lambda = E(\theta^2)/E(h^2) \ . \tag{3.19}$$

It follows that

$$E(\theta z_k) \quad = \quad \beta_k E(\theta^2) = \beta_k \lambda E(h^2) = \lambda E(hz_k) \quad \text{for all } z_k \in z \tag{3.20}$$

where the first equality uses the population estimate of β_k in terms of θ, the second equality uses the definition of λ, and the third equality uses the population estimate of β_k in terms of h. We restate the model in (3.12) with the proxy h adjusted by λ as

$$y \quad = \quad \lambda h\delta_\theta + z\delta_z + \omega \tag{3.21}$$

where

$$\omega \quad = \quad (\theta - \lambda h)\delta_\theta + \nu \ . \tag{3.22}$$

With (3.16) and (3.20), we have two sets of orthogonality conditions which identify the model:

$$E(h\eta) \quad = \quad E[h(y - h\delta_\theta - z\delta_z)] = 0 \tag{3.23}$$

$$E(z'\omega) \quad = \quad E[z'(y - \lambda h\delta_\theta - z\delta_z)] = 0. \tag{3.24}$$

The second orthogonality condition effectively multiples the covariance of z with the proxy h by the variance ratio λ to get the implied covariance of z with θ.

The estimator of δ will be based on the sample estimates of the proxy h and the true-to-proxy variance ratio λ. We can implement this GMM estimator because we have an estimate of λ from the maximum-likelihood estimation. This situation contrasts with standard errors-in-variables setting where the true-to-proxy variance ratio is unidentified. Substituting the sample analogs into the moment conditions and solving for the estimates gives

$$\begin{bmatrix} \widehat{\delta}_\theta \\ \widehat{\delta}_z \end{bmatrix} = \begin{bmatrix} N^{-1}\sum h_i^2 & N^{-1}\sum h_i z_i \\ N^{-1}\sum \lambda z_i' h_i & N^{-1}\sum z_i' z_i \end{bmatrix}^{-1} \begin{bmatrix} N^{-1}\sum h_i y_i \\ N^{-1}\sum z_i' y_i \end{bmatrix}. \tag{3.25}$$

Under the conditions specified, these will be consistent estimates of δ and have a limiting normal distribution. Note the ratio λ in the lower left block of the inverted matrix. There are three cases in which this estimator is identical to the OLS estimator: first, when there are no regressors other than risk tolerance; second, when none of the other regressors are correlated with true risk tolerance; and third, when there is no expectation error for the proxy, i.e., $\theta = h$, so $\lambda = 1$. Taking into account that the proxy variance is attenuated with respect to the true preference parameter is important in multivariate models with strong correlations between the other regressors and risk tolerance.

The asymptotic distribution of the estimator in (3.25) is

$$\sqrt{N}(\widehat{\delta} - \delta) \quad \rightarrow_D \quad N(0, A^{-1}BA^{-1}) \tag{3.26}$$

where

$$A = E\begin{bmatrix} h^2 & hz \\ \lambda z'h & z'z \end{bmatrix}, B = E\left[\begin{pmatrix} h\eta \\ z'\omega \end{pmatrix}\begin{pmatrix} h\eta & z'\omega \end{pmatrix}\right]. \tag{3.27}$$

While we do not directly observe risk tolerance, we can still compute an implied R^2 for the model in (3.12) based on the true values of risk tolerance. The R^2 as if true θ were observed is

$$R^2 = \frac{\widehat{\delta}' \begin{bmatrix} N^{-1}\sum \widehat{\lambda}\widehat{h}_i^2 & N^{-1}\sum \widehat{\lambda}\widehat{h}_i z_i \\ N^{-1}\sum \widehat{\lambda} z_i'\widehat{h}_i & N^{-1}\sum z_i' z_i \end{bmatrix} \widehat{\delta}}{N^{-1}\sum y_i^2}. \tag{3.28}$$

Using the standard R^2 from a regression with the proxy would understate the explanatory power of the model, since the variability of the proxy understates the true variability of risk tolerance. Table 3.6 shows that this understatement is substantial. The ratio λ of the variance of the true risk tolerance to the proxy is 6.32. When the other regressors are strongly correlated with risk tolerance, the GMM estimator in (3.25) and the implied R^2 in (3.28) will more accurately characterize the effects of risk tolerance on behavior than standard estimators. Even in a univariate regression on risk tolerance alone, equation (3.28) is needed to calculate the implied R^2.

3.6 APPLICATION TO ASSET ALLOCATION

In this section, we apply the methods discussed above to study asset allocation. Faced with uncertain asset returns, risk preferences should be central in allocating financial wealth between high risk and low risk assets. Individuals with greater risk tolerance should be willing to hold a larger fraction of their wealth in risky assets, such as stocks. Under complete markets, only risk tolerance and the distribution of risky asset returns affect allocations (Samuelson 1969, Merton 1969). Many individuals also anticipate labor income, which cannot be capitalized due to moral hazard and adverse selection. With market incompleteness, models of asset allocation also identify a role for the determinants of future labor income, such as age and the distribution of income shocks (Heaton and Lucas 1997). Empirical studies often document substantial differences in asset allocation by gender, education, and race. Nonetheless, much of the heterogeneity in asset allocation remains unexplained.

In contrast with other empirical studies of asset allocation, our risk tolerance proxy allows us to control quantitatively for the effects of risk preference cross-sectionally. In this section, using data from the HRS, we present estimates of how the share of financial wealth held in stocks increases with risk tolerance. We also consider other regressors such as gender, education, age, race, household income and wealth. While households typically own assets jointly, many of these attributes are person-specific. We treat the respondent who is most knowledgeable about household finances as the primary decision-maker and control for his or her attributes. We limit our analysis to households with positive financial wealth and income. Since the HRS is a sample of older households who have often accumulated some wealth, this selection eliminates fewer observations than it would in an age-representative sample. Nonetheless, it does exclude approximately 20% of households. The average share of financial wealth in stocks (excluding individual retirement accounts) is 0.16 and a significant portion of households do not own stocks. The standard deviation of the share in stocks is 0.29, so there is considerable dispersion in stock allocations.

To demonstrate the usefulness of our risk tolerance proxy h and the true-to-proxy variance ratio λ, we contrast our GMM estimates with the OLS estimates that use the risk tolerance variable without taking into account response error. While focusing on the effects of risk tolerance, we also discuss the effects of gender and education. We use the estimated effects from these regressors to demonstrate the misleading inferences from failing to take into account risk tolerance heterogeneity and also failing to correct for the consequences of survey response error in the risk tolerance proxy.

As a baseline, we estimate the stock allocation model without any control for risk tolerance. This corresponds to the approach in most empirical studies. As reported in Table 3.7, the gender, education, and race of the financial respondent as well as the household's log income and log financial assets account for 17.0% of the variation in stock allocations.

In this specification, households with men responsible for the finances have 2.4 percentage points more in stocks on average. Post-college education raises the share by 3.4 percentage points. Both are statistically significant and represent 15% and 22% of the average stock allocation.

If any of these characteristics correlate with risk tolerance, then their estimated coefficients also include the indirect effects of risk tolerance. One way to try to sort out the direct effects of risk tolerance on stock holding and to study the confounding effect of gender, education and other regressors is to estimate a model of asset allocation controlling for the categorical survey responses to the income gambles. Based on their first response in the HRS, we assign individuals to four risk tolerance categories. This regression with categorical controls explains 17.2% of the variation in stock allocations. Households in the most risk tolerant category hold 2.5 percentage points more of their wealth in stocks than those in the least risk tolerant category. But the relationship is nonlinear as households in the second lowest risk tolerant category hold 2.6 percentage points less in stocks than those in the least risk tolerant category. Adding the categorical controls diminishes the effect of a male financial respondent to 2.3 percentage points and post-college education to 3.2. These results are consistent with the Barsky et al. (1997) finding that men and the most educated are more risk tolerant. Even partially controlling for risk preferences begins to lower the estimated effect of these attributes on asset allocation.

The last four columns of estimates in Table 3.7 use different versions of the cardinal proxy for risk tolerance and different estimators. In the third column, we use the proxy from Section 3.3, which ignores survey response error. All else equal, the most risk tolerant households based on one observation (risk tolerance of 3.687) average 2.9 percentage points more in stocks than the least risk tolerant households (risk tolerance of 0.049).

The fourth column of Table 3.7 uses the proxy from Section 3.4 that accounts for the measurement error in the gamble responses but does not address the potential correlation between the proxy's expectation error and the other regressors discussed in Section 3.5.

These results show that ignoring survey response error greatly understates the marginal effect of risk tolerance on stock allocations. When we use the proxy values from Section 3.4, the coefficient estimate for the proxy increases over ten-fold. This increase shows how attenuation bias affects the estimates in the previous two columns that do not account for response error. Of course, this correction mainly scales up the coefficient estimate and does not affect the R^2. The larger estimated effect of risk tolerance means that when risk tolerance is measured more precisely with multiple responses that the predicted differences in behavior can be substantial. The most risk tolerant households based on multiple observations (risk tolerance of 0.732) average 9.4 percentage points more wealth in stocks than the least risk tolerant (risk tolerance of 0.087). This difference represents 60% of the average stock share. Thus correcting for measurement error has a substantial impact on the estimated responsiveness of behavior to risk tolerance.

The fifth column of Table 3.7 uses the same proxy for risk tolerance as in the fourth column but replaces the OLS estimator with the GMM estimator derived in Section 3.5. The GMM estimates show the importance of accounting for the correlation between the expectation error of the proxy and the other regressors. Using formula (3.28) for the implied R^2, the explained variation in stock allocations rises to 17.8% from 17.1%. The point estimate for the effect of risk tolerance rises 11% to 0.162. The average difference in stock allocations of the most and least risk tolerant households with multiple responses increases over one percentage point to 10.5. The GMM estimator has a more pronounced effect on the coefficient estimates for other regressors. As stressed in Section 3.5, the main issue is that in the OLS estimate the other regressors will spuriously account for variation in the dependent variable to the extent that they are correlated with risk tolerance. Having a male financial respondent now raises stock allocations by only 1.4 percentage points and the effect of a post-college education falls to 1.2 percentage points. These coefficient estimates are 42% and 65% lower than in the regression with no measure of risk tolerance and are no longer statistically different from zero at the 5% level.

As a check on the accuracy of the GMM estimator, the last column of Table 3.7 looks at an alternative estimator. Instead of basing the proxy just on the gamble response categories, we also condition on the regressors in this application. Specifically, in the first-step maximum-likelihood, we model the mean of log risk tolerance μ as a linear function of the observables z. The estimated unconditional mean and variance of log risk tolerance from this alternative first-step maximum-likelihood model are reported in the last column of Table 3.3. The estimated distribution does not differ substantially from the model that conditions on only the gamble responses. This is a direct approach to eliminate the correlation between the proxy's expectation error and the observables. Condition (3.15) now holds with equality and the OLS estimator with this new proxy consistently estimates the model with true risk tolerance. The last two columns of Table 3.7 are very similar. This finding implies that the GMM approach, which does not rely on re-estimating the proxy conditional on all the covariates in the regressions, works well.

The results in Table 3.7 demonstrate the importance of carefully controlling for the heterogeneity in preferences. Beyond using the proxy to control for heterogeneity in risk tolerance, we show how the effect of other regressors can be overstated if no correction is made for the fact that the proxy is imperfectly measured and the other regressors are correlated with preferences. For researchers who want to include an individual measure of risk tolerance in their studies of other behaviors, our maximum-likelihood estimates provide a valid proxy. To the extent that this proxy's expectation error is correlated with other explanatory variables of interest, the OLS estimates can be misleading. This problem can be addressed with the GMM estimator that we derive in Section 3.5 or can be avoided by conditioning on the other variables in the first-step maximum-likelihood. While the second alternative might be the best approach, the Health and Retirement Study is currently the only data set with a sufficient panel to correct for the survey response error in the gamble responses. When the first-step maximum-likelihood is not possible (for example, because of having only one response per individual), the proxy values we provide that condition only on the gamble responses should be used with the GMM estimator to obtain consistent estimates.

3.7 CONCLUSION

We demonstrate the importance of carefully controlling for risk preferences when examining asset allocation. In particular, our procedures address many issues in using survey-based measures of risk tolerance — translation of categorical responses to a cardinal metric, survey response error, and expectation error for the proxy. Our methods for constructing the proxy and estimating the effects of risk tolerance on behavior have a wide range of potential applications. A growing number of surveys including the Panel Study of Income Dynamics in the United States, the CentERpanel in the Netherlands, and the Social Security Survey in Chile have fielded lifetime income gambles like those in the HRS. Our statistical procedures for constructing the risk tolerance proxy can be applied with minimal adjustment to these other surveys.

In studies of asset allocation (Vissing-Jorgensen 2002) and intergenerational wealth correlations (Charles and Hurst 2003), researchers have used indicator variables from income gamble responses. This approach does not fully capture the effect of heterogeneous risk preferences. According to our empirical analysis, even if the direct effects of risk tolerance are not central to the study, such indicator variables are unlikely to adequately control for risk tolerance. In other words, these partial controls are not sufficient either in theory or practice for consistent estimates of the direct effects of other variables of interest. With survey questions and statistical techniques motivated by economic theory, we expand the options for studying the effects of risk preferences on behavior. Using the quantitative proxy for risk tolerance, we find a strong effect of risk tolerance on stock holding. Moreover, after accounting for how errors in measured risk tolerance are correlated with other variables, the estimated effects of gender and education on asset allocation are substantially reduced.

ACKNOWLEDGMENTS

This chapter is co-authored with Miles S. Kimball and Matthew D. Shapiro. The authors thank John Bound, Yuriy Gorodnichenko, John Laitner, Atsushi Inoue, Lutz Kilian, Tyler Shumway, Martha Starr-McCluer, Serena Ng, Gary Solon, seminar participants at Osaka University, and anonymous referees for helpful comments. The authors gratefully acknowledge the support of National Institute on Aging grants 2-P01-AG10179 and 5-R01-AG020638.

APPENDIX: BOOTSTRAP

Both the OLS and GMM estimates in Table 3.7 use the risk tolerance proxy h, which is a generated regressor from the first-step maximum-likelihood procedure. The variance ratio λ is another generated regressor in the GMM estimator. While the coefficient estimates from these second-step estimators are asymptotically consistent, the estimated standard errors do not reflect the sampling variation in the proxy and the variance ratio. We use a bootstrap to show this sampling variation does not qualitatively alter our inferences in Section 3.6.

Using a Monte Carlo experiment, we draw 199 random samples from the data and repeat the two steps of estimation in Section 3.4 and Section 3.6. Sampling with replacement, we maintain the distribution of respondents to the original and status-quo-bias-free questions. We use a symmetric t-test to construct the 95% bootstrap confidence on the proxy coefficient estimate in the asset allocation model. The OLS estimate in the fourth column of Table 3.7 of 0.146 has a confidence interval of 0.036 to 0.256. The GMM estimate of in the fifth column of Table 3.7 0.162 has a confidence interval of 0.040 to 0.284. In both cases, the estimated effect of risk tolerance on asset allocation remains statistically significant at the 5% level. As expected, sampling variation in the generated regressors has little effect on the inference of the other controls. The moderate impact of the generated regressors reflects the precision of the first-step maximum likelihood procedure.

Table 3.1: Risk Tolerance Response Categories

Response Category	Downside Risk of Risky Job: Accepted	Downside Risk of Risky Job: Rejected	Bounds on Risk Tolerance: Lower	Bounds on Risk Tolerance: Upper
1	None	1/10	0	0.13
2	1/10	1/5	0.13	0.27
3	1/5	1/3	0.27	0.50
4	1/3	1/2	0.50	1.00
5	1/2	3/4	1.00	3.27
6	3/4	None	3.27	∞

NOTE: Respondents choose between a job with a certain income and a job with risky income. With equal chances, the risky job will double lifetime income or cut it by the specific fraction shown in the columns labelled downside risk. The largest risk accepted and smallest risk rejected across gambles define a response category. In 1992 there are four categories 1-2, 3, 4, and 5-6. In 1994 and later surveys, there are six response categories. The last two columns show the bounds on relative risk tolerance consistent with these response categories in the absence of response error.

Table 3.2: Distribution of Risk Tolerance Responses

Response Category	% by HRS Wave 1992	1994	1998	2000	2002
1	64.6	43.4	37.9	46.3	44.8
2		18.1	19.0	18.4	18.6
3	11.6	13.5	17.0	14.4	15.3
4	10.9	14.5	10.8	8.1	9.6
5	12.9	6.3	8.0	7.5	6.1
6		4.2	7.3	5.3	5.6
Responses	11,592	717	796	884	3,591

NOTE: Tabulations use responses on the final release version of HRS 1992, 1994, 1998, 2000, and 2002 without sample weights. The sample for this paper includes the 11,616 original respondents in the HRS study who answer a gamble in one of the first two waves. See Table 3.1 for definition of the risk tolerance response categories.

Table 3.3: Distribution of Log Risk Tolerance: Maximum Likelihood Estimates

	Ignoring Response Error	Modeling Response Error	Including Application Covariates
Log Risk Tolerance			
Mean μ	-1.98	-1.84	-1.86
	(0.03)	(0.03)	(0.07)
Standard Deviation σ_x	1.76	0.73	0.73
	(0.03)	(0.04)	(0.04)
Status Quo Bias b_o		-0.11	-0.10
		(0.04)	(0.07)
Response Error Standard Deviation			
Original Question, Transitory σ_{eo}		1.39	1.40
		(0.05)	(0.05)
Original Question, Persistent $\sigma_{\kappa o}$		0.73	0.72
		(0.10)	(0.10)
SQB-Free Question, Transitory σ_{ef}		1.43	1.42
		(0.03)	(0.03)
SQB-Free Question, Persistent $\sigma_{\kappa f}$		0.60	0.61
		(0.09)	(0.09)
Number of Individuals	11,616	11,616	11,616
Number of Responses	11,616	17,580	17,580
Number of Parameters	2	7	19
Log-Likelihood	-12073.4	-21208.3	-21121.3

NOTE: The first column estimates the model in Section 3.3. The second column models survey response error, as described in Section 3.4. The model of log risk tolerance in the third column includes the covariates from the application in Section 3.6. Asymptotic standard errors are in parentheses.

Table 3.4: Distribution of Risk Preferences

	Log Risk Tolerance	Risk Tolerance	Risk Aversion
Mean	-1.84	0.206	8.2
	(0.03)	(0.009)	(0.3)
Median	-1.84	0.159	6.3
	(0.03)	(0.005)	(0.2)
Mode	-1.84	0.094	3.7
	(0.03)	(0.004)	(0.2)
Std. Dev.	0.73	0.172	6.8
	(0.04)	(0.018)	(0.7)
Fractiles			
1	-1.54	0.029	1.2
5	-1.32	0.048	1.9
10	-1.20	0.063	2.5
25	-1.01	0.097	3.9
50	-0.80	0.159	6.3
75	-0.59	0.259	10.3
90	-0.40	0.402	16.0
95	-0.28	0.523	20.8
99	-0.07	0.858	34.1

NOTE: The values are calculated from the parameter estimates in the the second column of Table 3.3. Asymptotic standard errors approximated with the delta method are in parenthesis.

Table 3.5: Imputation of Risk Preference

Response Category	Log Risk Tolerance	Risk Tolerance	Risk Aversion
1	-2.107	0.153	10.4
2	-1.811	0.203	7.6
3	-1.693	0.228	6.7
4	-1.575	0.257	6.0
5	-1.419	0.301	5.1
6	-1.172	0.387	4.0

NOTE: The proxy values are for responses to a single SQB-free question and are based on the estimates in the second column of Table 3.3. The values differ for persons answering in multiple surveys, the original question type, or in the combined categories 1-2 and 5-6. We provide a spreadsheet of all possible values online (http://www.umich.edu/∼shapiro/data/risk_preference).

Table 3.6: True-to-Proxy Variance Ratio λ

	Estimate
Variance	
Risk Tolerance θ	0.030
Proxy $h = E(\theta\|c)$	0.005
True-to-Proxy Ratio λ	6.319

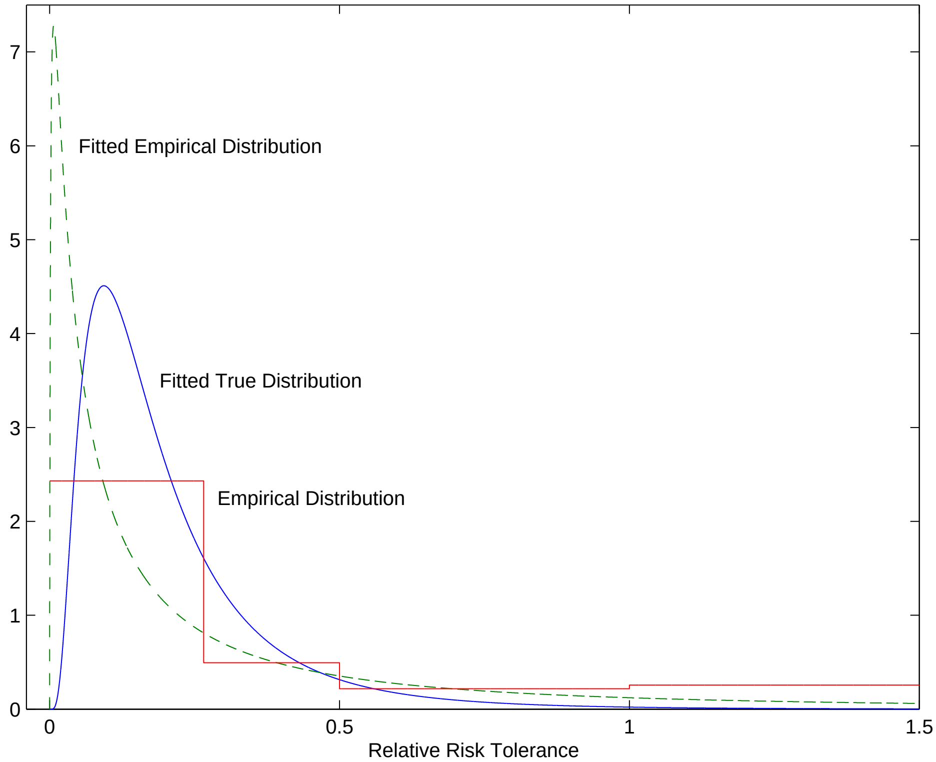
NOTE: The estimated variance of true risk tolerance and its proxy depend on the estimated parameters in the second column of Table 3.3. Section 3.4 describes the relationship between survey responses and the proxy values. The true-to-proxy variance ratio λ is an input to the GMM estimator in (3.25) and the R^2 in (3.28).

Table 3.7: Effect of Risk Preferences on the Share of Financial Wealth in Stocks

			Risk Tolerance Proxy			
Control for Log Risk Tolerance	None	Categorical Survey Response	Ignoring Response Error	Modeling Response Error	Modeling Response Error	Including Application Covariates
Estimator	OLS	OLS	OLS	OLS	GMM	OLS
Category 3		**-0.026**				
		(0.010)				
Category 4		0.022				
		(0.012)				
Category 5-6		**0.025**				
		(0.011)				
Proxy			**0.008**	**0.146**	**0.162**	**0.152**
			(0.003)	(0.054)	(0.060)	(0.056)
Male	**0.024**	**0.023**	**0.023**	**0.023**	0.014	**0.018**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Education						
> 16 Years	**0.034**	**0.032**	**0.032**	**0.031**	0.012	0.019
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.014)
13-16 Years	**0.036**	**0.035**	**0.035**	**0.035**	**0.024**	**0.029**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
< 12 Years	**-0.023**	**-0.024**	**-0.023**	**-0.023**	**-0.026**	**-0.024**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Black	**-0.029**	**-0.029**	**-0.029**	**-0.028**	**-0.024**	**-0.027**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Hispanic	**-0.035**	**-0.036**	**-0.035**	**-0.035**	**-0.034**	**-0.038**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)
Age / 10	-0.002	-0.001	-0.001	-0.001	0.006	0.006
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Log Income	0.002	0.003	0.003	0.002	0.004	0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Log Wealth	**0.046**	**0.047**	**0.046**	**0.046**	**0.047**	**0.046**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R^2	0.170	0.172	0.171	0.171	0.178	0.178

NOTE: Regressions include 5,818 households with positive financial wealth and total income in 1992. Individual attributes are from the household's financial respondent. Share of wealth in stocks has a mean of 0.158 and a standard deviation of 0.286. Estimated coefficients in bold are statistically significant at the 5% level. Asymptotic standard errors are in parentheses. In the second to last column the GMM estimates are based on the formula in (3.25) and the R^2 in the last two columns is based on the formula in (3.28). For the application sub-sample, the true-to-proxy variance ratio λ is 6.40. In the last column, the proxy is constructed from a model of log risk tolerance that conditions on the application covariates as well as the gamble responses.

Figure 3.1: Distribution of Relative Risk Tolerance



NOTE: The solid line shows the empirical distribution of the survey responses. The solid curve shows the fitted distribution of the true level of risk tolerance: $\theta = \exp(x)$ using the model from Section 3.4. The dashed curved shows the fitted empirical distribution: $\exp(\xi) = \exp(x + \epsilon)$.

CHAPTER IV

Labor Income and Heterogeneity in Household Portfolios

4.1 INTRODUCTION

There is considerable heterogeneity in the degree of risk that households assume in their financial portfolios, yet the underlying sources of these differences are not well understood.[1] A large number of households with financial assets do not own any stocks directly in spite of the high average return on stocks relative to riskless assets. In contrast, a modest fraction of stock owners hold most of their financial assets in stocks. These patterns highlight the wide disparity in financial portfolios across households. There are a number of possible candidates to explain this heterogeneity, such as differences in risk tolerance, fixed costs of stock ownership or other barriers to entry that vary across households, and differences in the riskiness or magnitude of households non-financial wealth. Previous empirical research has found some evidence for each of these explanations, albeit typically in reduced-form estimation and with much of the observed variation in portfolios left unexplained.[2]

In this paper, I quantify the amount of variation in financial portfolios explained by measured differences in risk preference and human capital. Specifically, I compare the actual stock allocation of households with their predicted allocation from a fully parameterized, structural model. While the models of asset allocation that I examine are well established

[1] A recent volume (Guiso, Haliassos and Jappelli 2002) and chapter (Curcuru, Heaton, Lucas and Moore 2005) on household portfolios provide a comprehensive overview of the literature and references. While there are some well established patterns in household portfolios, such as the more educated tend to hold more risky assets, there is no consensus on the mechanism behind this association.

[2] As examples of this work, Barsky et al. (1997) and Kimball et al. (2007) establish a positive relationship between risk tolerance and the share of financial assets held in stocks. Vissing-Jorgensen (2002) estimates that a low level of annual fixed costs could explain a large portion of non-participation. Several papers provide some evidence that individuals with riskier human capital hold less risky financial portfolios (Vissing-Jorgensen 2002, Heaton and Lucas 2000, Guiso, Jappelli and Terlizzese 1996).

in the literature, my approach in the empirical analysis is novel.[3] I use detailed information in the Health and Retirement Study (HRS) and administrative earnings records to establish parameter values at the household level for risk preference, the distribution of future labor income, and the ratio of current financial assets to labor income. For each household in my sample, I solve three standard models that differ only in their treatment of labor income and obtain the predicted stock allocations.

The comparison of actual stock allocations and the model predictions confirms a role for the differences in risk preference; however, there is little evidence that households integrate their human capital in financial portfolio decisions. In the first model where households only differ in their risk preference, the correlation of the model prediction with actual stock allocations is 0.16. When the model includes a certain flow of future labor income, the correlation drops sharply to -0.12. So the households that the second model predicts to have above average stock allocations are, in fact, the households who have below average stock allocations in the data. The intuition for the model prediction is that households with large amounts of riskless human capital relative to their financial assets should tilt their financial assets toward risky assets to achieve a desired allocation in their total wealth (human capital plus financial assets). As a result, the model with labor income tends to assign high stock allocations to households with low levels of financial assets. These are exactly the households who are least likely to actually own stocks. The third model which incorporates the riskiness of future labor income does soften this result, but the correlation between the actual and predicted allocations is still negative at -0.06. Even when the household-specific measures of labor income risk are increased by 50% the correlation between the actual and predicted stock allocation only increases to 0.02. Altogether, my results provide strong evidence against the systematic integration of human capital in households' financial portfolios.[4]

[3]Scholz et al. (2006) is a recent example of household-specific calibration in the retirement saving literature. Numerical models in the portfolio choice literature, such as Cocco et al. (1997), are typically calibrated for a representative agent or for a small number of agent groups, such as education groups.

[4]My results are consistent with other research in portfolio choice and recent events that also provide evidence against the integration of human capital, such as holding of own-company stocks, as in the well-publicized case of Enron, and not holding foreign company stocks (home bias) that are less correlated with own human capital than domestic company stocks.

The plan of the paper is as follows. Section 4.2 documents the heterogeneity in household financial portfolios. Section 4.3 then describes three standard models of asset allocation. Section 4.4 uses information in the HRS to calibrate the models at the household level. Section 4.5 compares the model predictions to actual behavior. The final section offers conclusions.

4.2 HETEROGENEITY IN FINANCIAL PORTFOLIOS

I use the Health and Retirement Study (HRS) with its rich demographic and financial information to investigate the heterogeneity in household financial portfolios.[5] A study of older households is actually well suited to understanding differences in asset allocation, since a larger fraction of these older households have financial assets to invest than would be the case in studies with younger households. Even as these older households in the HRS approach retirement and accumulate more financial assets, their current and expected labor income remains an important component of their total household wealth.

Table 4.1 describes the stock allocation of households in the HRS from 1992 to 2002. The average share of financial assets held directly in stocks increases from 0.19 in 1992 to 0.26 in 1998 and then declines to 0.24 in 2002.[6] These tabulations only include households with financial assets of at least $1,000 (2002 dollars), since asset allocation — not saving — is the behavior of interest. Table 4.1 also reveals differences across households in their stock allocations. The standard deviation of the stock allocations is always greater than 0.30 and the coefficient of variation exceeds 140% in each survey wave. The percent of households who own stocks does increases over the period, but the stock owners never represent a majority of the households. Interestingly, a modest fraction of the stock owners (between 27% and

[5]The Health and Retirement Study began in 1992 as a large biennial panel survey of Americans over the age of 50 and their spouses. Further information on the survey and the data are available at http://hrsonline.isr.umich.edu.

[6]The stock allocation of the household is defined as the ratio of its stocks to its financial assets. Stocks include the net value of stocks in publicly held corporations, mutual funds; or investment trusts. Financial assets include stocks plus the money in checking or savings accounts or money market funds; CDs, government savings bonds or Treasury bills; corporate, municipal, government or foreign bonds or bond funds corporate bonds; and other savings or assets, such as valuable collection, annuity or trust. The assets held in Individual Retirement Accounts, Keoghs, or employer pensions are not included in the measure of stock allocation. The information needed to roughly allocate retirement assets between high and low risk assets is only available in the 1998 and later waves of the HRS. If IRAs and private pensions were included, a majority of households would have some exposure to the stock market; however, there is a strong positive correlation between the direct ownership of stocks and ownership of stocks in retirement accounts or pensions.

44%) have stock allocations of 0.75 or higher. The patterns in asset allocation among HRS households is qualitatively similar to results from the Survey of Consumer Finances which includes a wider age-range of households (Heaton and Lucas 2000, Bertaut and Starr-McCluer 2002).

Starting with the bottom panel of Table 4.1, the rest of this paper focuses on a younger sub-sample of HRS households who also receive labor earnings.[7] Specifically, the sub-sample of earners follows HRS households with an initial primary earner in the 1938-1941 birth cohorts as long as the household reports at least $6,500 in labor earnings. The initial primary earner is the member of the household with more labor earnings in the 1992 HRS. Among couples, the main earner is more likely to be male, is slightly older than the spouse, and has roughly the same level of education as the spouse. The selection criteria for the sub-sample of earners are restrictive, especially in the later survey waves, so the bottom panel of Table 4.1 includes only 23% to 10% of the households in the top panel. Yet, the patterns in the stock allocations of the earner sub-sample are very similar to the patterns of all HRS households, despite the selection criteria. Regardless of how one cuts the data, there is considerable heterogeneity in the financial portfolios across households.

4.3 MODELS OF ASSET ALLOCATION

In this section, I describe three models of asset allocation that differ only in their treatment of labor income. In each of the three models, a household chooses current consumption C_{it} and stock allocation α_{it} to maximize its lifetime utility, such that

$$\max_{C_{it},\alpha_{it}} \quad E_t \sum_{j=t}^{T} \beta^{j-t} \left(\prod_{k=t}^{j-1} p_k \right) \frac{C_{it}^{1-\gamma_i}}{1-\gamma_i} \tag{4.1}$$

$$\text{s.t} \quad X_{i,t+1} = \left(R_b + \alpha_{it}(R_{s,t+1} - R_b)\right) F_{it} + Y_{it+1} \tag{4.2}$$

$$F_{it} = X_{it} - C_{it} \tag{4.3}$$

$$0 \leq \alpha_{it} \leq 1 \ , \tag{4.4}$$

[7]The labor earnings of the household combine the individual labor earnings of the financial respondent and his spouse or partner. The labor earnings include any wage and salary income; bonuses, overtime, tips, and commissions; income from professional practice or trade; and other income from a second job or military reserves.

where p_t is a one-year survival probability, β is the utility discount factor, and γ_i is the coefficient of relative risk aversion. The household allocates its total resources X_{it} between consumption C_{it} and the purchase of financial assets F_{it}. There are two financial assets: riskless bonds with a one-period gross real return of R_b and stocks with an uncertain gross real return $R_{s,t+1}$. The share of financial assets allocated to stocks is α_{it}. In addition to the gross returns from financial assets, the total resources of next period may include labor income Y_{it+1}. No short-selling of stocks or margin purchases is permitted, so the stock allocation α_{it} is between zero and one.

4.3.1 Model with No Labor Income

In the absence of labor income, that is, $Y_{it} = 0 \ \forall \ i$ and t, only risk preference and the risk-return characteristics of stocks affect asset allocation (Samuelson 1969). Assuming stock returns $R_{s,t+1}$ are log-normally distributed, an analytical solution for the stock allocation α_{it} exists. Specifically, the share of financial assets in stocks is

$$\alpha_{it}^N = (1/\gamma_i)\frac{E_t(R_{s,t+1}) - R_b}{\sigma_s^2} \ . \tag{4.5}$$

The first term on the right is the inverse coefficient of relative risk aversion and summarizes the household's willingness to bear risk. The allocation also depends on the ratio of the expected excess return on stocks $E_t(R_{s,t+1}) - R_b$ and the variance of stock returns is σ_s^2. With time-constant risk preferences and distributional assumptions on asset returns, a household maintains this same allocation regardless of age or realized stock returns. This model with no labor income only predicts heterogeneity in financial portfolios when households differ in their risk preferences or expectations regarding asset returns.

4.3.2 Model with Certain Labor Income

For many households labor income is an important source of non-financial income that should be integrated in their decisions about consumption and asset allocation. Assume that labor income process follows a deterministic process, such that:

$$Y_{i,t+1} \quad = \quad G_{i,t+1}Y_{it} \tag{4.6}$$

where the household knows the full set of future growth factors $G_{i,t+1}, ...G_{iT}$ and income Y at age t. When future labor income is certain, the adjustment of the households' financial portfolios is straightforward (Merton 1971). Specifically, a household with financial assets F_{it} and a present discounted value of future labor income $PDV_{it}(Y)$ chooses a stock allocation of

$$\alpha_{it}^{C} = \frac{\alpha_{it}^{N}(F_{it} + PDV_{it}(Y))}{F_{it}} \tag{4.7}$$

$$\text{where,} \qquad PDV_{it}(Y) = \sum_{j=t+1}^{T} R_b^{t-j} \left(\prod_{k=t}^{j-1} p_k \right) Y_{ij}$$

$$= Y_{it} \sum_{j=t+1}^{T} R_b^{t-j} \left(\prod_{k=t}^{j-1} p_k G_{i,k+1} \right) . \tag{4.8}$$

The household discounts its stream of riskless future labor income with the riskless bond return R_b and the one-year survival probabilities p_t. With any positive amount of labor income and holding the other parameters constant, the stock allocation α_{it}^{C} is always higher than the stock allocation α_{it}^{N}. This higher share of financial assets in stocks α_{it}^{C} allows the share of total wealth (financial assets plus human capital) in stocks to remain at α_{it}^{N}. The adjustment of the financial portfolio is most dramatic for households with low levels of financial assets relative to their future labor income. When financial assets are a very large portion of the household's total wealth, there is little difference between the predicted allocations of the two models. The introduction of certain labor income means that heterogeneity in financial portfolios can arise from differences in preferences, as well as differences in the ratio of current financial assets to labor income and the expected path of future labor income.

4.3.3 Model with Risky Labor Income

Future labor income is rarely predictable over long horizons, so economic theory has long recognized that the riskiness of labor income and other background factors should affect asset allocation (Merton 1971, Mayers 1974). Suppose that next year's labor income $Y_{i,t+1}$ depends on the current labor income Y_{it}, a predictable growth factor $G_{i,t+1}$, and a random shock $\epsilon_{i,t+1}$ up until retirement at age τ. After retirement, the household receives an income each year equal to a fraction rr_i of its income in the final working income, such that,[8]

$$Y_{i,t+1} = \begin{cases} G_{i,t+1} Y_{it} \epsilon_{i,t+1} & t < \tau \\ rr_i Y_{i\tau-1} & t \geq \tau \end{cases} . \tag{4.9}$$

In this parsimonious model of anticipated labor income, all shocks ϵ while working are permanent, so labor income growth follows a random walk with a drift. Labor income shocks and the excess return on stocks follow a joint log normal distribution, where

$$\begin{bmatrix} \log(\epsilon_{it}) \\ \log(R_{st}) \end{bmatrix} \sim N\left(\begin{bmatrix} -\sigma_i^2/2 \\ \mu_s \end{bmatrix}, \begin{bmatrix} \sigma_i^2 & \rho_i\sigma_i\sigma_s \\ \rho_i\sigma_i\sigma_s & \sigma_s^2 \end{bmatrix} \right) . \tag{4.10}$$

On average, labor income follows its predictable growth path, i.e., $E(\epsilon_{it}) = 1$, however, a working household also anticipates income shocks with volatility σ_i and correlation with stock returns ρ_i. There is no labor income risk in retirement.

The household maximization problem is now expressed in a value function with total resources X_{it} and labor income Y_{it} as the state variables, such that

$$V_{it}(X_{it}, Y_{it}) = \max_{C_{it}, F_{it}, \alpha_{it}^R} \frac{C_{it}^{1-\gamma_i}}{1-\gamma_i} + p_t \beta E_t[V_{i,t+1}(X_{i,t+1}, Y_{i,t+1})] \tag{4.11}$$

$$X_{i,t+1} = \left(R_b + \alpha_{it}^R (R_{s,t+1} - R_b)\right) F_{it} + Y_{i,t+1} \tag{4.12}$$

$$0 \leq \alpha_{it}^R \leq 1 . \tag{4.13}$$

This value function is homogenous of degree $(1-\gamma_i)$, so dividing through by current income reduces the state space to the ratio of total resources to labor income. For a household before retirement the optimization problem is

$$V_{it}(x_{it}) = \max_{c_{it}, f_{it}, \alpha_{it}^R} \frac{c_{it}^{1-\gamma_i}}{1-\gamma_i} + \beta p_t G_{i,t+1}^{1-\gamma_i} E_t[\epsilon_{i,t+1}^{1-\gamma_i} V_{i,t+1}(x_{i,t+1})] \tag{4.14}$$

$$x_{i,t+1} = (R_b + (R_{s,t+1} - R_b)\alpha_{it}^R) f_{it}/(G_{i,t+1}\epsilon_{i,t+1}) + 1 \tag{4.15}$$

$$0 \leq \alpha_{it}^R \leq 1 . \tag{4.16}$$

The relationship between the value functions is $V_{i,t+1}(x_{i,t+1}) = Y_{it}^{\gamma_i - 1} V_{it}(X_{it}, Y_{it})$, where c_{it}, f_{it}, and x_{it} are consumption, financial assets, and total resources all normalized by current

[8]This simple specification of the labor income process is similar to the one used in Cocco et al. (1997).

labor income. In the restated model, the values relative to labor income are important, not absolute levels. The solution to the model yields the following consumption Euler equation and first-order condition for stock allocation:

$$c_{it}^{-\gamma_i} = \beta p_t G_{i,t+1}^{-\gamma_i} E_t[(R_b + (R_{s,t+1} - R_b)\alpha_{it}^R)(c_{i,t+1}\epsilon_{i,t+1})^{-\gamma_i}] \tag{4.17}$$

$$0 = E_t[(R_{s,t+1} - R_b)(c_{i,t+1}\epsilon_{i,t+1})^{-\gamma_i}] \ . \tag{4.18}$$

There is no analytical solution for the stock allocation α_{it}^R, so the model prediction at each age is solved numerically by backward induction. I use the solution method in Carroll (2002). Intuitively, households should view their future labor income (or human capital) as an implicit holding of risky and riskless assets. A household anticipating a relatively large, low risk stream of labor income should increase its explicit financial holding of stocks — as was the case in the model with certain labor income. In contrast a household, whose human capital, is as a large implicit holding of risky assets should offset these implicit risky assets in its financial portfolio. Regardless of how the labor income process is specified, risk preference remains fundamentally important and determines the optimal stock allocation of total household wealth. In this third model, the riskiness of labor income is an additional source of heterogeneity in financial portfolios.

4.4 HOUSEHOLD PARAMETERS

The predicted stock allocation from each of the theoretical models depends on numerous parameter values. Rather than study a "representative" household, I assign parameter values to each household based on their survey information. This allows me to compare actual behavior and the model predictions at the household level. My approach also differs from estimating the parameter values that maximize the fit between actual stock allocations and the model. The rich detail of the survey and matched administrative earnings records underpins this exercise.

4.4.1 Risk Preference

Risk preference is a key factor in any economic model of asset allocation and may vary considerably across households. I use the responses to hypothetical gambles in the HRS to estimate an individual measure of risk preference as in Barsky et al. (1997) and Kimball et al. (2007). The first column of Table 4.2 reports the estimated model of log risk tolerance estimated. Individuals with more education and higher average income are more risk tolerant, whereas blacks are less risk tolerant than whites. I use these maximum-likelihood estimates to compute the expected risk aversion γ of individuals conditional on their gamble responses. While most individuals are highly risk averse with a mean of 8.5, there is considerable dispersion in these survey-based risk preferences. The standard deviation of the risk aversion measure is 3.7 and there is a considerable range in the values from 1.1 to 21.1.

4.4.2 Current Financial Assets and Labor Income

In models with labor income, the predicted stock allocation depends on the ratio of current financial assets to labor income. The top panel of Table 4.3 displays the median values of these two variables across the first six HRS waves. All dollar amounts are converted to 2002 dollars with the CPI-U. The median value of financial assets increases from \$16,669 in 1992 to \$30,000 in 2002 but remains fairly modest. Even as the households approach retirement, labor earnings are an important component of their resources. The median value of labor earnings increases from \$55,475 in 1992 to \$57,252 in 1998 and then declines to \$48,758 in 2002. With these patterns in financial assets and labor earnings, the median ratio of financial assets-to-labor earnings starts at 0.31 in 1992 and increases to 0.55 in 2002. Many households expect future years of labor income, so these low ratios underscore the relative importance of human capital in the total wealth of the household.

The bottom panel of Table 4.3 repeats these calculations for the subset of households who directly own stocks. While median labor income is 19-24% higher than in the sample of earner households, the median stockholder has roughly 2-3 times more financial assets.

For stockholders, financial assets are much more important relative to labor income and this importance grows over the panel as the assets-to-earnings ratio increases from the 0.79 in 1992 to 1.38 in 2002.

4.4.3 Future Labor Income

The labor income that households expect to receive in the future or their human capital is another factor in the models of asset allocation that include labor income. There are parameters for the predictable growth of labor income and the ex-ante distribution of unpredictable income shocks. I use Social Security administrative records matched to the HRS to characterize labor earnings prior to retirement. The Wage and Self-employment Income (WSEI) file contains all the earned income that is reported by employers on W-2 forms and the self-employment income reported on IRS 1040 Schedule SE. A matched administrative earnings record for the 1980-1991 period is available for roughly 70% of HRS. The values on the administrative file are less prone to self-reporting errors and arguably of better quality than the HRS income reports. The high top-code of $125,000 on this particular version of the earnings records is binding for less than 0.4% of the income observations.

I estimate the parameters of the income process in equation (4.9) by pooling up to 11 years of real growth in individual earnings. For this analysis I use a larger sample of all original households who report some labor income in 1991. I combine wage and salary income, as well as self-employment income for both members of the household and convert to constant 1992 dollars using the CPI-U. To analyze the growth rates, I compute log differences and exclude any growth observation in which income more than triples or falls to one-third of its previous value. This prevents outliers from driving the estimates. I only include growth rates for households with a main earner ages 35 to 64 in 1991. The second column of Table 4.2 provides the estimated model of real earnings growth. Higher education increases the mean of earnings growth and there is a predictable decline in earnings growth with age. These coefficient estimates are used to construct a set of growth factors $G_{51} - G_{64}$ for each household based on the covariates of its primary earner.

The regression of earnings growth explains only a small fraction of the observed variance, so there are sizeable unpredictable movements in earnings growth. In the third column of Table 4.2, I regress the squared residuals from the earnings growth regression on a set of time-constant explanatory variables. The less educated, the more risk tolerant, women, and Hispanics have larger unpredictable movements in their earnings growth. Blacks have smaller variance in earnings growth than whites. These coefficient estimates are used to construct a household-specific value for the standard deviation of labor income shocks σ. The dispersion parameter has an average of 0.25 and ranges from 0.18 to 0.34.

The riskiness of labor income also depends on its covariation with the risky asset returns ρ. In the fourth column of Table 4.2 I estimate a model where the dependent variable is the product of the earnings growth residual and the demeaned real return on the S&P 500. The earnings of households with a male or black primary earner are more positively correlated with asset returns, but the estimated effects are small. I use these coefficient estimates to construct the households covariance between earnings shocks and stock returns and combine this with the variance of earnings shocks and returns to calculate the correlation parameter. The correlation is an average of 0.039 and ranges from -0.036 to 0.109.

I assume that all working households expect to retire at age 65 and that their post-retirement income maintain a fixed replacement rate (in real terms) of their final year of labor earnings. To assign this parameter, I calculate the average ratio of total household income (less capital income) in the first wave after retirement to the total household income in the previous wave by education group. I only use observations where the primary earner is age 64-66 at the time of retirement. The replacement rate of pre-retirement income is the highest for the least educated receive at 91% and the lowest for the most educated receive at 76%. I assign the household's replacement rate rr_τ based on the educational attainment of the main earner.

4.4.4 Parameters Common to All Households

I assign the remaining parameters values commonly to all households, including the time discount factor, survival probabilities, the risk-return characteristics of stocks, and the riskless bond return. While there is some subjective information in the HRS that could be used to assign these parameters at the household level, in this paper, I adopt standard values from other calibration studies.

I adopt the one-year survival probabilities from the U.S. National Center for Health Statistics. The age-specific probabilities, $p_{50} - p_{99}$, are from 1996 Life Tables for the total population. To characterize the survival probabilities, a 50-year-old has a 99.5% chance of reaching age 51, whereas an 80-year-old has a 94.0% chance of living another year. On average, a 50-year-old expects to live another 29 years. Thus a retirement age of 65 implies another 15 years of employment and 14 years in retirement on average. At age 100, I assume the probability of surviving another year is zero, i.e., $T = 100$. The age of the main earner determines the relevant survival probability for a household.

I assume that the riskless real return on bonds $\log(R_b)$ is 2% and the annual discount factor for utility β is 0.96. The average excess real return on stocks $\log(R_s)$ is 4% and the standard deviation of stock returns σ_s is 15.7%. The ex-ante distribution of asset returns does not vary over time or across households, thus I abstract from the potentially important differences in the subjective expectations of asset returns.

4.5 ACTUAL AND PREDICTED ALLOCATIONS

With the three model specifications and the household-specific parameter values, I now compute the predicted stock allocations for each household. With a model prediction for each household, I can assess the correspondence between the actual and predicted financial portfolios at the household-level. The different treatment of labor income in the three model also allows me to isolate the extent to which labor income can account for the observed heterogeneity in stock allocations.

The top panel of Table 4.4 compares the actual and predicted stock allocations for the earner households. For these tabulations, I pool 4,163 observations from 1,223 earner households in the first six survey waves. On average households allocate a 0.24 share of their financial assets to stocks. The model with no labor income predicts a slightly higher share of 0.25. When the model integrates labor income, the average prediction for the stock allocation increases considerably to 0.97 with certain income and 0.71 with risky income. The integration of labor income — a substantial increase in the implicit holdings of low risk assets — greatly exacerbates the micro version of the equity premium puzzle. Given the relative security of their future labor earnings, households should be willing to shift their financial assets toward stocks to take advantage of their excess return.

The second row of Table 4.4 reports the standard deviation in the actual and model stock allocations. The actual stock allocation has a large standard deviation of 0.34. The predictions from the model with no labor income is only half as disperse as the actual stock allocations with a standard deviation of 0.14. When labor income is certain the standard deviation of the predicted allocation decreases to 0.12, since many of the households have allocation at the upper bound of 1.0. Labor income risk creates substantial heterogeneity in the predicted stock allocations. The standard deviation of 0.33 is similar to the standard deviation of actual stock allocations. While the predictions from models with labor income over-state the average share of financial assets held in stocks, they do mimic the observed heterogeneity across households in their financial portfolios.

A more revealing test of the models is the correlation between the actual and predicted stock allocations reported in the third row of Table 4.4. The model that excludes labor income has the highest correlation of 0.16 with the actual allocations. The fit of this simple model is well below 1.0, but it affirms a positive association between risk tolerance and stock allocations. When certain labor income is added to the model, the correlation falls dramatically to -0.12. Riskiness in labor income improves the correlation, but it remains negative at -0.06. The last column shows that even a large increase in the riskiness of labor income, where the standard deviation of earnings shocks σ and their correlation with risky asset returns ρ are increased by 50% for each household, would only yield a small positive correlation of 0.02. These results suggest that the differences in labor income across households cannot explain the heterogeneity in stock allocations. There is no evidence that households integrate their human capital in their financial portfolio decisions.

The bottom panel of Table 4.4 repeats the calculations for the 672 households who own stocks. Given the low stock market participation rates this is a very selective group of households. The average share of financial assets allocated to stocks is 0.55 — more than double the average share among all earner households. In contrast, the predicted stock allocations for the stockholders in the models are quite similar to the predictions for the earner households in the top panel. All of the correlations between actual and predicted stock allocations are small and not statistically different from zero at the 5% level. In particular, this suggests that the variation in risk tolerance is more useful in predicting stock ownership than the share of financial assets in stocks. None of the models can account for the patterns in stock allocation among stock owners.

I use a regression analysis in Table 4.5 to highlight the factors that drive a wedge between the actual stock allocations of households and their model predictions. The goal is to identify the sources of the low correlation between the actual and predicted stock allocations. For each model, I regress the standardized product of the household's actual and predicted stock allocation on the household's level of financial assets, ratio of financial assets to labor income, and age of the main earner.[9] This provides a linear regression model for the correlation between actual and predicted stock allocation. Across all three models with different treatments of labor income, higher levels of household financial assets are associated with a higher correlation between actual and predicted stock allocations. None of the models include fixed costs for participation in the stock market, so the inability of the models to predict the low stock allocations of households with few financial assets is not surprising.

[9]For the standardized product, I subtract the sample mean of the actual and predicted allocation before calculating the product and then normalize this product by the product of the standard deviations for the actual and predicted allocations.

However, the absence of fixed costs in the models is just one reason for a poor fit between the model predictions and actual behavior. Among households with the same level of financial assets, there is also a lower correlation between the actual and predicted allocation for households with high levels of financial assets relative to their labor income. So even among households with high levels of financial assets — or those households for whom the absolute monetary costs of ignoring human capital are more substantial — there is evidence against the integration of human capital in the financial portfolio decision.

4.6 CONCLUSION

The direct comparison of actual stock allocations and predicted allocations from economic models with labor income shows that households do not systematically integrate their human capital in their financial portfolio decisions. An important feature of this analysis is the use of household-specific measures of both income risk and risk preference. The potential effects of heterogeneous risk preferences are typically not addressed in the empirical studies of asset allocation with human capital. Yet, there is empirical evidence that individuals select into riskier careers based on their risk preference (Fuchs-Schuendeln and Schuendeln 2005, Sahm 2007). Furthermore, the same level of income risk would have different effects across individuals with different levels of risk tolerance. If I constrain all households to have the average risk aversion of 8.5, the mean of the predicted allocations is unaffected, but the correlation between the model predictions with labor income and the actual stock allocation worsens considerably. The correlation falls to -0.19 from -0.12 with certain income and to -0.28 from -0.06 with risky income. These results underscore that the heterogeneity in risk preferences is an important source of the heterogeneity in financial portfolios.

Consistent with previous reduced-form estimation of asset allocation, I do find that households with riskier labor income hold less risky financial portfolios. However, if households made their investment decisions on the basis of total wealth, the average stock allocation in financial assets would be higher, particularly among households with low financial asset-to-labor earnings ratios. The implicit holdings of low risk assets in human capital result in a much larger equity premium puzzle. This outcome is trivial in the model with certain labor income, but is not guaranteed when labor income is risky. In particular, a sufficiently positive correlation between labor income growth and stock market returns could lead to less risky financial portfolios when human capital is included. Yet, the time series of household labor income in the HRS administrative earnings files does not show such patterns. The negative correlation between actual stock allocations and the predicted stock allocations in the models with labor income suggests that either human capital is not an important factor in the financial portfolio decision of households or is not adequately captured in the standard model.

With the expansion of defined contribution pensions and proposals to introduce individual accounts to Social Security, the asset allocation decisions of households will likely have an increasing impact on their financial resources and welfare in retirement. It is important to understand the actual sources of heterogeneity in financial portfolios, since the appropriate policy response, if any, would depend on the particular source. The results in this paper suggest that differences in risk preference across households and fixed costs of stock ownership likely account for some of the differences in actual stock allocations. While there are theoretically important differences across households in their human capital, the actual stock allocations of households do not reflect their human capital as economic theory predicts. Households who fail to take a broad view of their economic wealth may needlessly forgo the excess returns of stocks and may not properly diversify the risks in their human capital and financial assets. The end result of households not integrating their human capital is less and possibly more volatile financial resources in retirement.

ACKNOWLEDGMENTS

The author thanks Matthew Shapiro, Miles Kimball, Gary Solon, Tyler Shumway, Bob Barsky, John Bound, Chris House, Serena Ng, and participants at the 2005 Midwest Economic Association Annual Meeting and the 2005 Institute on Computational Economics for helpful comments on earlier drafts of the paper.

Table 4.1: Allocation of Financial Assets in Stocks, 1992-2002

	HRS Wave					
Stock Allocation	1992	1994	1996	1998	2000	2002
All Households						
Mean	0.19	0.22	0.24	0.26	0.26	0.24
Standard Deviation	0.30	0.32	0.34	0.36	0.36	0.35
% Greater than Zero	39	43	44	45	44	44
% 0.75 or Higher	10	13	15	17	18	16
Number of Households	5,366	4,954	4,718	4,547	4,471	4,311
Sub-Sample of Earners						
Mean	0.19	0.24	0.26	0.29	0.26	0.25
Standard Deviation	0.31	0.33	0.35	0.37	0.36	0.35
% Greater than Zero	39	43	46	48	44	43
% 0.75 or Higher	11	14	17	20	19	17
Number of Households	1,245	1,010	821	670	567	428

NOTE: Author's tabulations of the Rand HRS data set (Version D) use the household survey weights. The top panel includes all households in the HRS study group who report financial assets greater than $1,000 in 2002 dollars at a particular survey wave. The stock allocation is the ratio of the net value of stocks held directly by the household to its total financial assets (excluding IRAs). The bottom panel includes a sub-sample of the households in the top panel whose primary wage earner in 1992 is in the 1938 to 1941 birth cohorts and is still working at a particular survey wave. See the text for more details on the variable and sample definitions.

Table 4.2: Coefficient Estimates in Assignment of Model Parameters

	Dependent Variable			
Explanatory Variable	Log Risk Tolerance	Real Growth Rate of Earnings	Square of Unpredictable Earnings Growth	Product of Earnings Growth and Stock Returns
Constant	**-3.38**	**-0.309**	**0.071**	0.001
	(0.32)	(0.094)	(0.002)	(0.0004)
Male	0.05	0.0003	**-0.017**	**0.001**
	(0.04)	(0.003)	(0.002)	(0.0003)
Black	**-0.20**	0.006	**-0.013**	**0.001**
	(0.07)	(0.004)	(0.002)	(0.0005)
Hispanic	0.07	0.003	**0.026**	-0.001
	(0.09)	(0.005)	(0.003)	(0.0007)
High School Drop Out	0.01	0.003	**0.013**	0.0003
	(0.06)	(0.004)	(0.002)	(0.0005)
Some College	**0.17**	**0.007**	-0.00001	-0.001
	(0.05)	(0.004)	(0.002)	(0.0005)
College Graduate	**0.14**	**0.015**	0.0003	-0.001
	(0.07)	(0.005)	(0.003)	(0.0006)
Post Graduate	**0.26**	**0.016**	-0.012	-0.001
	(0.06)	(0.005)	(0.003)	(0.0005)
Average FEP	**1.16**			
	(0.11)			
Log of Average Income	**0.09**			
	(0.03)			
Fraction of Waves Married	-0.10			
	(0.06)			
Age		**0.014**		
		(0.004)		
$\text{Age}^2/100$		**-0.016**		
		(0.004)		
Risk Tolerance		0.007	**0.030**	0.001
		(0.014)	(0.009)	(0.0018)
Log-Likelihood	-20185.3			
R^2		0.003	0.006	0.001
Number of Individuals	11,255	4,039	4,039	4,039
Number of Observations	16,851	39,741	39,741	39,741
Used to Assign Parameter	γ	G	σ	ρ

NOTE: Asymptotic standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. The maximum-likelihood estimation in the first column uses the hypothetical gamble responses from 1992-2002 and allows heteroscedasticity in the survey response error. Fraction exact probability is the fraction of subjective probability questions to which the respondent gave a non-focal answer (not 0, 50, or 100). Averages in the first column are calculated for an individual over up to six survey waves. The OLS estimation of the earnings process in the last three column uses the matched Social Security administrative earnings records from 1980-1991.

Table 4.3: Current Financial Assets and Labor Earnings

	Median Value in HRS Wave					
	1992	1994	1996	1998	2000	2002
Earner Households						
Financial Assets	16,669	24,278	23,505	28,641	24,028	30,000
Labor Earnings	55,475	54,779	57,252	54,923	52,911	48,758
Assets-to-Earnings Ratio	0.31	0.43	0.42	0.49	0.46	0.55
Number of Households	1,245	1,010	821	670	567	428
Stockholder and Earner						
Financial Assets	56,419	55,233	58,989	78,361	91,820	84,250
Labor Earnings	66,043	64,739	70,827	65,011	62,360	59,628
Assets-to-Earnings Ratio	0.79	0.81	0.84	1.26	1.52	1.38
Number of Households	449	415	352	303	232	172

NOTE: All dollar values are converted to 2002 dollars with the CPI-U. See text for the definition of financial assets and labor earnings.

Table 4.4: Comparison of Actual and Predicted Stock Allocations

		Labor Income in Model			
	Actual	None	Certain	Risky	Riskier
Earner Households					
Mean	0.24	0.25	0.97	0.71	0.47
Standard Deviation	0.34	0.14	0.12	0.33	0.37
Correlation with Actual	1.00	0.16	-0.12	-0.06	0.02
		(0.02)	(0.02)	(0.02)	(0.02)
Stockholders					
Mean	0.55	0.28	0.95	0.69	0.48
Standard Deviation	0.31	0.16	0.14	0.32	0.35
Correlation with Actual	1.00	0.01	-0.04	-0.04	-0.03
		(0.02)	(0.03)	(0.02)	(0.02)

NOTE: Asymptotic standard errors are in parentheses. Pooling across 1992-2002 waves, there are 4163 observations from 1223 Earner Households and 1810 observations from 672 Stockholders. See the text for details on the model specification. The last column analyzes the predicted allocation from the model with risky labor income where the assigned parameters of labor income risk (σ and ρ) have been inflated by 50%.

Table 4.5: Decomposition of Stock Allocation Correlations

	Dependent Variable		
	Product of Actual and Predicted by Labor Income		
Explanatory Variables	None	Certain	Risky
Log of Financial Assets	**0.042**	**0.136**	**0.081**
	(0.015)	(0.020)	(0.013)
Asset-to-Earnings Ratio	0.003	**-0.213**	**-0.085**
	(0.012)	(0.032)	(0.011)
Age / 10	0.038	-0.001	-0.021
	(0.048)	(0.057)	(0.044)
Constant	-0.482	**-1.210**	**-0.650**
	(0.305)	(0.377)	(0.270)
R^2	0.004	0.114	0.025

NOTE: Asymptotic standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. The product of the demeaned actual stock allocation and the demeaned predicted stock allocation for each household are divided by the standard deviation of the actual and predicted allocation in the pooled cross-section.

CHAPTER V

Conclusion

The three papers in this dissertation explore the measurement of individual risk tolerance and its usefulness in understanding asset allocation. The first two papers improve on the estimation techniques for inferring the coefficient of relative risk tolerance from the hypothetical income gambles on the Health and Retirement Study. The third paper employs this measure of risk tolerance in a test of whether households integrate their human capital in their financial portfolio decisions. The research in this dissertation contributes to a growing literature on the survey-based measurement of individual preference parameters and recognizes the fundamental impact of individual preferences and cognitive abilities on economic behavior.

BIBLIOGRAPHY

Barsky, Robert B., F. Thomas Juster, Miles S. Kimball, and Matthew D. Shapiro, "Preference Parameters and Behavioral Heterogeneity: An Experimental Approach in the Health and Retirement Study," *Quarterly Journal of Economics*, 1997, *112* (2), 537 – 579.

Bertaut, Carol and Martha Starr-McCluer, "Household Portfolios in the United States," in Luigi Guiso, Michael Haliassos, and Tullio Jappelli, eds., *Household Portfolios*, MIT Press Cambridge, MA 2002, pp. 181–218.

Breeden, Douglas T., "An Intertemporal Asset Pricing Model with Stochastic Consumption and Investment Opportunities," *Journal of Financial Economics*, 1979, *7* (3), 265–296.

Brunnermeier, Markus K. and Stefan Nagel, "Do Wealth Fluctuations Generate Time-Varying Risk Aversion? Micro-Evidence on Individuals' Asset Allocation," December 2006. Working Paper.

Byrnes, James P., David C. Miller, and William D. Schafer, "Gender Differences in Risk Taking: A Meta-Analysis," *Psychological Bulletin*, 1999, *125* (3), 367–383.

Camerer, Colin F. and Robin M. Hogarth, "The Effects of Financial Incentives in Experiments: A Review and Capital-Labor Production Framework," *Journal of Risk and Uncertainty*, 1999, *19* (1), 7–42.

Cameron, Colin A. and Pravin K. Trivedi, *Microeconometrics: Methods and Applications*, New York: Cambridge University Press, 2005.

Carroll, Christopher D., "Lecture Notes on Solution Method for Microeconomic Stochastic Optimization Problems," 2002.

____ **and Miles S. Kimball**, "Precautionary Saving and Precautionary Wealth," *The New Palgrave: A Dictionary of Economics*, 2007.

Chamberlain, Gary, "Panel Data," in Z. Griliches and M.D. Intriligator, eds., *Handbook of Econometrics*, Elsevier Science Publishers BV Amsterdam 1984, pp. 1248–1318.

Charles, Kerwin K. and Erik Hurst, "Intergenerational Wealth Correlations," *Journal of Political Economy*, 2003, *111* (6), 1155–1182.

Cocco, Joao F., Francisco J. Gomes, and Pascal J. Maenhout, "Consumption and Portfolio Choice over the Life-Cycle," *The Review of Financial Studies*, 1997, *18* (2).

Curcuru, Stephanie, John Heaton, Deborah Lucas, and Damien Moore, "Heterogeneity and Portfolio Choice: Theory and Evidence," in Yacine Ait-Sahalia and Lars P. Hansen, eds., *Handbook of Financial Econometrics*, Elsevier Science Amsterdam 2005.

Dohmen, Thomas J., Armin Falk, David Huffman, Uwe Sunde, Juergen Schupp, and Gert Georg Wagner, "Individual Risk Attitudes: New Evidence from a Large, Representative, Experimentally-Validated Survey," February 2006. CEPR DP No. 5517.

Donkers, Bas, Bertrand Melenberg, and Arthur Van Soest, "Estimating Risk Attitudes Using Lotteries: A Large Sample Approach," *Journal of Risk and Uncertainty*, 2001, *22* (2), 165–195.

Friend, Irwin and Marshall E. Blume, "The Demand for Risky Assets," *AER*, December 1975, *65* (5), 900–922.

Fuchs-Schuendeln, Nicola and Matthias Schuendeln, "Precautionary Savings and Self-Selection: Evidence from the German Reunification Experiment," *Quarterly Journal of Economics*, 2005, *120* (3), 1085–1120.

Gertner, Robert, "Game Shows and Economic Behavior: Risk-Taking on Card Sharks," *Quarterly Journal of Economics*, May 1993, *108* (2), 507–521.

Guiso, Luigi, Michael Haliassos, and Tullio Jappelli, *Household Portfolios*, Cambridge, Massachusetts: MIT Press, 2002.

____ , Tullio Jappelli, and Daniele Terlizzese, "Income Risk, Borrowing Constraints, and Portfolio Choice," *American Economic Review*, 1996, *6* (1), 158 – 172.

Hall, Brownwyn H., Jacques Mairesse, and Laure Turner, "Identifying Age, Cohort and Period Effects in Scientific Research Productivity: Discussion and Illustration Using Simulated and Actual Data on French Physicists," June 2005. Working Paper.

Harrison, Glenn W., Eric Johnson, Melayne M. McInnes, and E. Elisabet Rutstroem, "Temporal stability of estimates of risk aversion," *Applied Financial Economic Letters*, 2005, *1* (1), 31–35.

Heaton, John and Deborah Lucas, "Market Frictions, Savings Behavior, and Portfolio Choice," *Macroeconomic Dynamics*, 1997, *1* (1), 76–101.

____ and ____ , "Portfolio Choice and Asset Prices: The Importance of Entrepreneurial Risk," *The Journal of Finance*, 2000, *55* (3), 1163 – 1198.

Holt, Charles A. and Susan K. Laury, "Risk Aversion and Incentive Effects," *The American Economic Review*, 2002, *92* (5), 1644–1655.

Howrey, E. Philip, "The Predictive Power of the Index of Consumer Sentiment," *Brookings Papers on Economic Activity*, 2001, *2001* (1), 175–207.

Kézdi, Gabor and Robert J. Willis, "Who Becomes A Stockholder? Expectations, Subjective Uncertainty, and Asset Allocation," February 2006. Working Paper.

Kimball, Miles S., Matthew D. Shapiro, and Claudia R. Sahm, "Imputing Risk Tolerance from Survey Responses," April 2007. Working Paper.

Lillard, Lee and Robert Willis, "Cognition and Wealth: The Importance of Probabilistic Thinking," June 2001. Michigan Retirement Research Center Working Paper 2001-007.

Mayers, David, "Portfolio Theory, Job Choice and the Equilibrium Structure of Expected Wages," *Journal of Financial Economics*, 1974, *1* (1), 23–42.

Merton, Robert C., "Lifetime Portfolio Selection under Uncertainty: The Continuous-time Case," *Review of Economics and Statistics*, 1969, *51* (3), 247–257.

____ , "Optimal Consumption and Portfolio Rules in a Continuous Time Model," *Journal of Economic Theory*, 1971, *3* (4), 373–413.

Miranda, Mario J. and Paul L. Fackler, *Applied Computational Economics and Finance*, The MIT Press, 2002.

Mundlak, Yair, "On the Pooling of Time Series and Cross Section Data," *Econometrica*, January 1978, *46* (1), 69–85.

Post, Thierry, Martijn J. Van den Assem, Guido Baltussen, and Richard H. Thaler, "Deal or No Deal? Decision Making Under Risk in a Large-Payoff Game Show," May 2006. Working Paper.

Pratt, John W., "Risk Aversion in the Small and in the Large," *Econometrica*, 1964, *32* (1/2), 122–136.

Ruhm, Christopher, "Are Workers Permanently Scarred by Job Displacements?," *American Economic Review*, 1991, *81* (1), 319–324.

Sahm, Claudia R., "Stability of Risk Preference," 2007. Working Paper.

Samuelson, Paul A., "Lifetime Portfolio Selection by Dynamic Stochastic Programming," *Review of Economics and Statistics*, 1969, *51* (3), 239–246.

Samuelson, William and Richard Zeckhauser, "Status Quo Bias in Decision Making," *Journal of Risk and Uncertainty*, 1988, *1* (1), 7–59.

Scholz, John Karl, Ananth Seshadri, and Surachai Khitatrakun, "Are Americans Saving 'Optimally' for Retirement?," *Journal of Political Economy*, August 2006, *114* (4).

Smith, James P., "Consequences and Predictors of New Health Events," October 2003. NBER Working Paper No. 10063.

Stephens, Melvin, "The Long-Run Consumption Effects of Earnings Shocks," *Review of Economics and Statistics*, 2001, *83* (1), 28–36.

Stigler, George J. and Gary S. Becker, "De Gustibus Non Est Disputandum," *American Economic Review*, 1977, *67* (2), 76–90.

Thaler, Richard H. and Eric J. Johnson, "Gambling with the House Money and Trying to Break Even: The Effects of Prior Outcomes on Risky Choice," *Management Science*, June 1990, *36* (6), 643–660.

Vissing-Jorgensen, Annette, "Towards an Explanation of Household Portfolio Choice Heterogeneity: Nonfinancial Income and Participation Cost Structures," 2002. NBER Working Paper No. 8884.